INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

Data Analysis in Healthcare Automation Using Computer Vision

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OPEN ACCESS

Received: 08-08-2024

Accepted: 08-05-2025

Published: 30-05-2025

Editor: Special Issue Editors: Dr. N. Pothanna, Dr.T. Jayashree, Dr. V. Ganesh Kumar

Citation: Mahalakshmi KV, Vishnu P, Venkateshkumar R, Raja H, Narayanan KL (2025) Data Analysis in Healthcare Automation Using Computer Vision. Indian Journal of Science and Technology 18(SP1): 37-44. https://doi.org/10.17485/IJST/v18si1.icamada27

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Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Abstract

Objectives: To apply computer vision techniques in healthcare automation and analysis and assist medical professionals. **Methods:** The proposed work encapsulates computer vision techniques; such as traditional computer vision technique using contour detection, Machine Learning-Based Computer vision techniques and clustering techniques. The Machine Learning (ML)-based Computer vision techniques include; Support Vector Machine (SVM) and Logistic Regression (LR). The methodology uses Magnetic Resonance imaging scans of brain, Ovarian and hepatic tumors, focusing on parameters like region of interest, accuracy of classification to determine the behavior of the algorithm. The traditional method has successfully detected the Tumor region and created a bounding box to showcase the region. The method uses concept of thresholding and contour detection. **Findings:** The Machine learning (ML)-based computer vision uses Classification algorithm such as Support Vector Classifier (SVC) and Logistic Regression (LR), which classifies the testing image data into its respective tumor subtype. After classification, by leveraging thresholding and contour detection techniques, our Region of Interest (ROI) which is, the tumor region is detected with a bounding box. SVC attains an accuracy of 86.3% and Logistic regression attains an accuracy of 82%. The clustering algorithms such as K-Means, successfully detected the glioma tumor regions and cancer image datasets including Hepatic and Ovarian cancer. **Novelty:** The proposed methodology classifies the tumor images into their respective tumor sub-groups and the tumor affected area can be highlighted with the computer vision techniques like bounding boxes simultaneously.

1 Introduction

The healthcare industry consists of a vast array of organizations, professionals and technologies-based services dedicated to maintenance of patient health. Hospital care, healthcare providers, medical equipment that design and provide surgical machines for detection and diagnosis of ailments effectively. Medical Imaging scans, especially tumour scans such as MRI or PET scan are subjected to visual inspection by doctors and radiologists to detect tumours. Doctors, especially radiologists are trained to recognize general anatomy and abnormalities in the scan. Masses or lesions, irregular shaping and contrast enhancement are giveaways for visual detection of tumours. Even with advanced imaging of MRI scans, tumours can be missed when detecting in this manner. Small or growing tumours may not be visible entirely to the human eye, misinterpretation of such tumours as regular masses or lack of proper contrast dye that does not light up the tumour. Human error or fatigue can also be one of the most definitive causes of false negatives. The detection of a potentially life-threatening anomaly is based up on expertise and visualization alone. Computer aided diagnostics, Computer Vision plays a superior role in accurate detection and diagnosis. Hospital care, healthcare providers, medical equipment that design and provide surgical machines maintaining supply and demand, pharmaceuticals involved in research and development of drugs to manage diseases. Medical professionals diagnose conditions by visually examining scan images for abnormalities. With Computer Vision, it can assist healthcare officials to simplify this process with high accuracy[(1)]. The field of Computer vision combines Magnetic Resonance Imaging (MRI) scans (data) and computer vision techniques (technology) to create a path-breaking solution which can benefit the healthcare professionals primarily[(2)].

These days, AI based computer-aided detection assist in analysis and diagnosis of abnormalities with an accuracy higher than that of registered medical professional viewing[(3)]. This review highlights such methods to do the same mainly using computer vision[(4–6)]. Computer Vision is a field of artificial intelligence that enables computers to understand visual information around them, this is achieved by a bunch of algorithms and interpretation techniques[(7–9)]. Additionally, these classification algorithms are used to detect, classify and highlight the affected area for ovarian cancer[(10,11)].

These classification algorithms mainly include; Support vector classifier[(12)], Logistic Regression[(13)], K-Nearest Neighbors, Random Forest. Due to simplicity and efficiency of Support Vector classifier and Logistic Regression, they are highly preferred for brain tumor detection applications[(14)]. In computer vison, Clustering methods like K-means clustering can be applied to detect glioma tumors, Ovarian Cancers and Hepatic Cancers, where variability of pixel intensity is high.

2 Methodology

2.1 Traditional Computer Vision Technique

The traditional Computer Vision technique includes encapsulating the concepts and methods of thresholding and contour detection. While thresholding, the raw image is converted into a binary image, which forms a new image where the tumor region is shown predominantly and with contour detection, the area within the given contour area range can be detected and labelled using the bounding box.

2.2 Machine Learning (ML) Based Computer Vision

There are mainly three types of ML based detection – Supervised[(15)], Unsupervised[(15)] and Reinforcement learning[(7)]. Supervised learning refers to an algorithm where the model associates an input with a label, to make a relationship between inputs and categorized labels[(16)] Unsupervised learning trains an input to match with unlabeled data, this is done to discover secret patterns or relationships between data that have not been explored, wherein reinforcement data is a reward- penalty system that has agents to interact with the environment, each right move is rewarded and a wrong move is penalized. In this proposed methodology, we use classification algorithms like support vector machine (SVM)[(12,13)], which is supervised learning and unsupervised learning algorithms like K-means clustering[(1)].

2.2.1 Dataset analysis

Table 1. Overview of the data used in ML- Based Computer Vision

Type of Tumor and the folder name	Number of images	
	Training Data	Testing Data
Normal	238	200
Pituitary_tumor	444	383
Glioma_tumor	601	300
Meningioma_tumor	613	299

Dataset Link: https://www.kaggle.com/datasets/aastharana/brain-tumor-detection-using-mri-images

Dataset Link (Hepatic): https://mma.prnewswire.com/media/833495/Pseudocolor_accentuated_CT_scan_image_of_a_liver_tumor.jpg?p=publish

The dataset consists of 3078 images of MRI scans with tumor and no tumor. Then these images are divided into 4 types of files; Normal, Pituitary_tumor, Glioma_tumor and Meningioma_tumor. Additionally, Ovarian and Hepatic cancers were considered separately. The segmented 3078 images are again segmented to training data and testing data files, consisting of 1896 and 1182 images respectively.

2.2.2 Support Vector Machine (SVM)

Support Vector Machine is a supervised algorithm used in machine learning to solve tasks relating classification and regression [12]. It works to find the best boundary between two classifications, this boundary is known as hyperplane. By increasing the margin, it gets easier to distinguish and classify objects. This method encapsulates uses of several key components to achieve its objectives. It consists of NumPy for efficient numerical computations, OpenCV (cv2) for image processing, Matplotlib for visualization of results. Additionally, it integrates Principal Component Analysis (PCA) for feature extraction and finally Support Vector Classification (SVC) for classification of brain tumors. The code encompasses importing classes pertaining to types of brain tumor – Normal (none), Pituitary, glioma, meningioma. It is then subjected to concatenation, splitting and reduction and resizing as a function of OpenCV (cv2) and further to principle component analysis (PCA), SVC is imported classifying the reconditioned scan images, additionally providing accuracy test results. SVC plays the role of segmenting the testing images to its respective tumor group, predicts it, and labels it using computer vision techniques [4].

2.2.3 Logistic Regression

Logistic regression is a machine learning based statistical method used in image segmentation and analysis [2]. It is a binary classification algorithm working on a greyscale scan, giving two outputs – normal or tumor indicative. Before LR application, the scan is subjected to feature extraction and trained on labelled medical dataset. Thresholding and principal component analysis is applied to the trained scan. This is now tested in model prediction and evaluated on the basis of results [13].

2.2.4 Clustering Data Visualization

K-means is a machine learning algorithm used to cluster data into groups or clusters. The algorithm initializes centroids to represent the centers of clusters. A data point is allotted to closest centroid based on distance (Euclidean). The centers of data points are recalculated a couple of times until a fixed value of group centers is attained. Once stabilization of centers has occurred, clusters are formed. This method helps find patterns in a particular dataset without having prior knowledge of the case. K- means is commonly used as a heart data analytics visualization tool. This done by choosing risk variables, normalizing the data to the same scale, choosing clusters and applying the algorithm to cluster heart disease data [5].

3 Results and Discussion

3.1 Traditional Computer Vision Technique

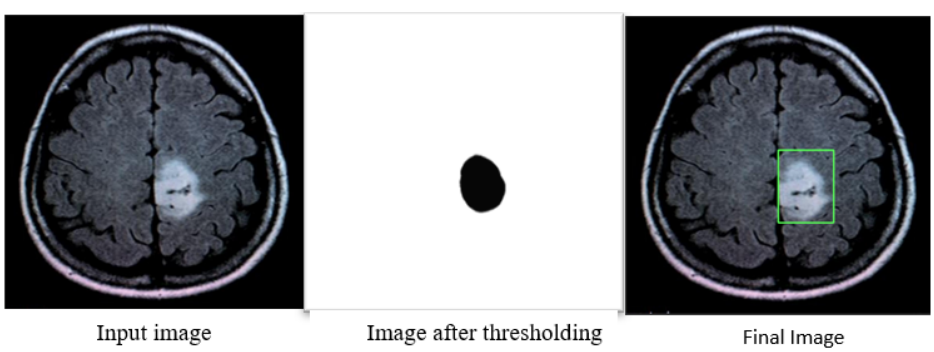

Fig 1. Traditional Computer Vision technique

The input MRI scan (Figure 1) is taken first. Then it is converted into a binary image using the method of thresholding. After thresholding, the image that is formed (Figure 1) will be our region of interest. After that, using Contour detection method, and with the help of contour area parameter, the desired range of contour and intensity region gets detected and labelled using the bounding box (Figure 1). This method primarily emphasizes the importance of thresholding and contour detection and its role in detecting our region of interest, which is the tumor affected area. The value of the threshold value in this scan is 100, and it can vary, with respect to the intensity of the MRI Scan image.

3.2 Machine Learning (ML) Based Computer Vision:

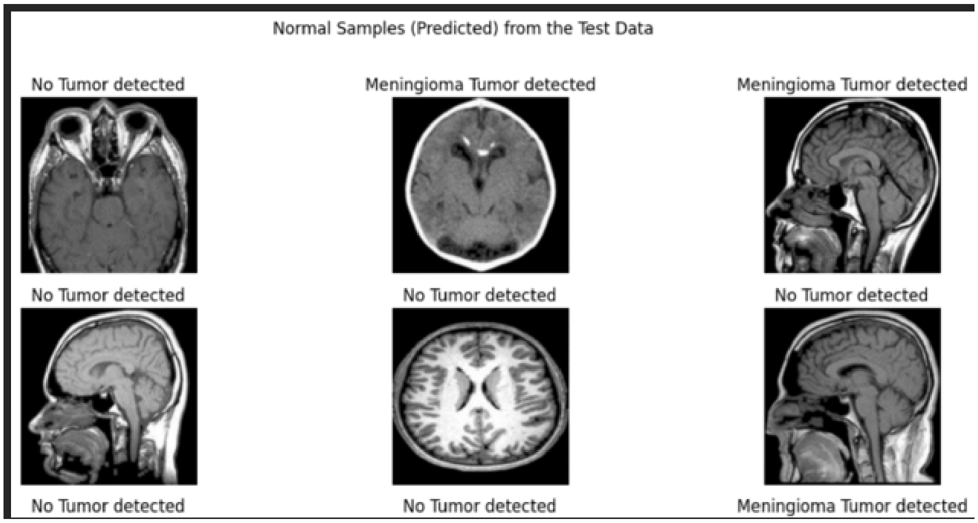

Fig 2. Segmented and labelled images showing the test data image belonging to "Normal tumor samples" or no-tumor subgroup

In ML-Based computer Vision, there are two steps; segmenting and labelling. The Support Vector Classifier [12,13] and Logistic Regression [13] both segment and predicts the testing MRI scans to their tumor sub group. After that, labelling happens. In labelling, the region of interest, which is the tumor affected area gets detected and labelled using thresholding and contour detection. The final images for no tumor subgroup (Figure 2), pituitary tumor subgroup (Figure 3) and Meningioma tumor (Figure 4) are labelled and shown.

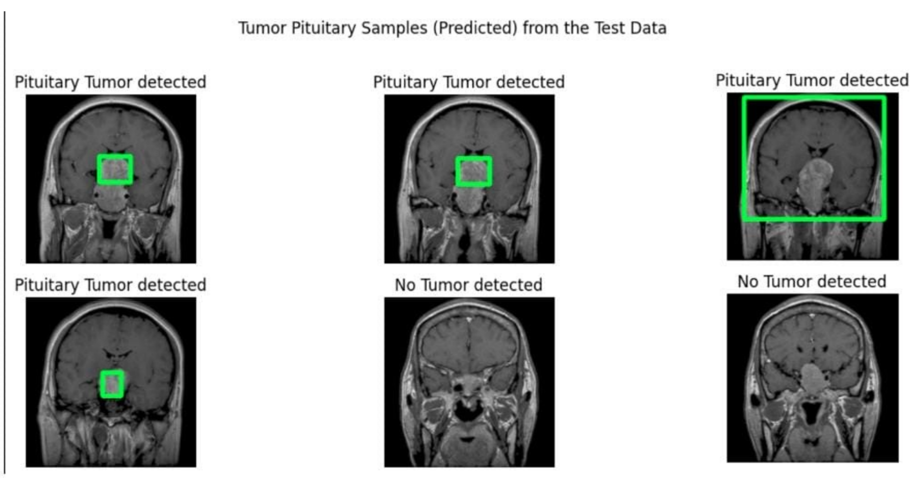

Fig 3. Segmented and labelled images showing the test data image belonging to "Pituitary tumor samples" or pituitary tumor subgroup. The tumor affected region is labelled using bounding box

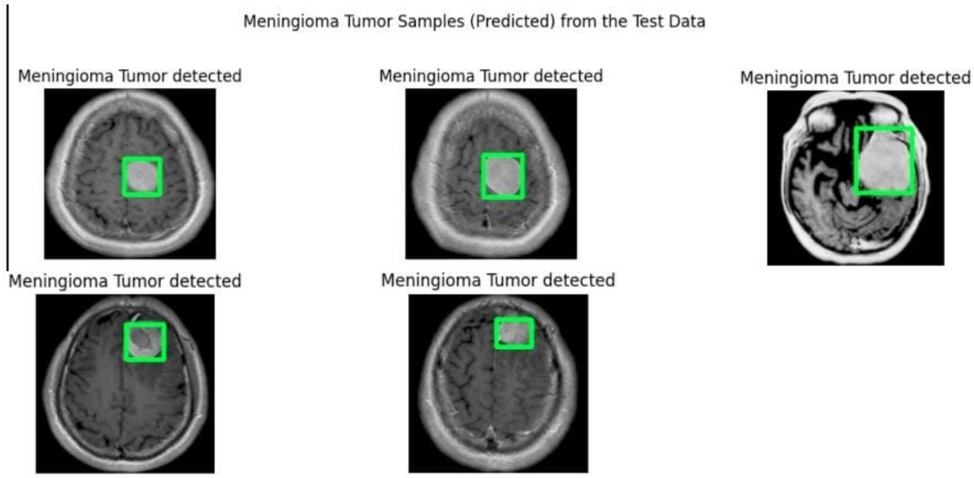

Fig 4. Segmented and labelled images showing the test data image belonging to "Meningioma tumor samples" or meningioma tumor subgroup. The tumor affected region is labelled using bounding box

The figures (Figure 2, Figure 3, Figure 4) have identified its region of interest and accurately highlights the tumor affected area, with the help of bounding boxes after they are classified into sub-types based on the machine learning algorithms, Support Vector classifier or Logistic Regression. The bounding boxes have efficiently highlighted the presence of Pituitary tumors and meningioma tumors in the scan.

3.3 Clustering Data Visualization (or) K-Means Clustering Method:

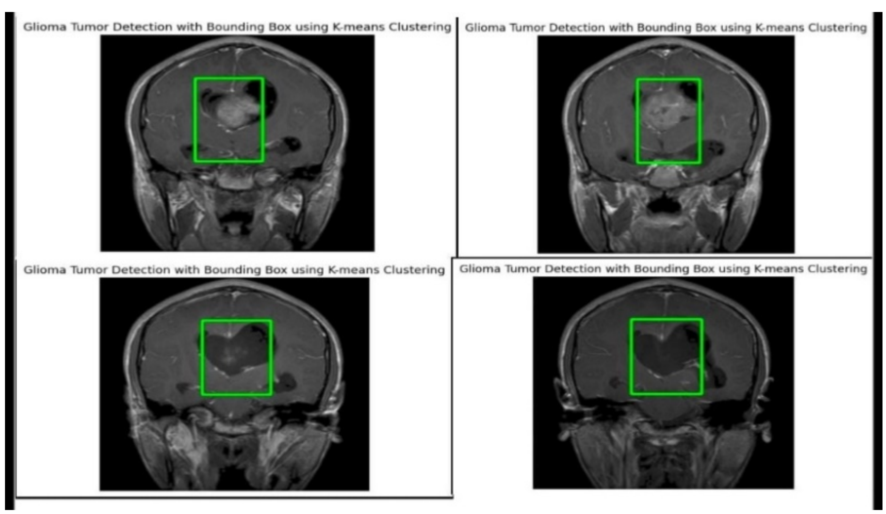

Fig 5. Segmented images showing the test data image belonging to "Glioma tumor samples" or pituitary tumor subgroup. The tumor affected region is labelled using bounding box, using K-means clustering method

The K-Means clustering approach clearly marvels at detecting the glioma tumor from the scans, as shown in Figure 5. Additionally, the approach has been used to detect ovarian cancers (Figure 6) and Hepatic Cancer (Figure 7). The K-Means Clustering process segments the "tumor" and "non-tumor" and uses bounding box to visually highlight the tumor affected area.

From (Figure 5, Figure 6, Figure 7), it is evident that the scans with higher variability in pixels can be easily detected and highlighted using the K-Means clustering method. Here we have used the value K as 2, which achieved an effective output.

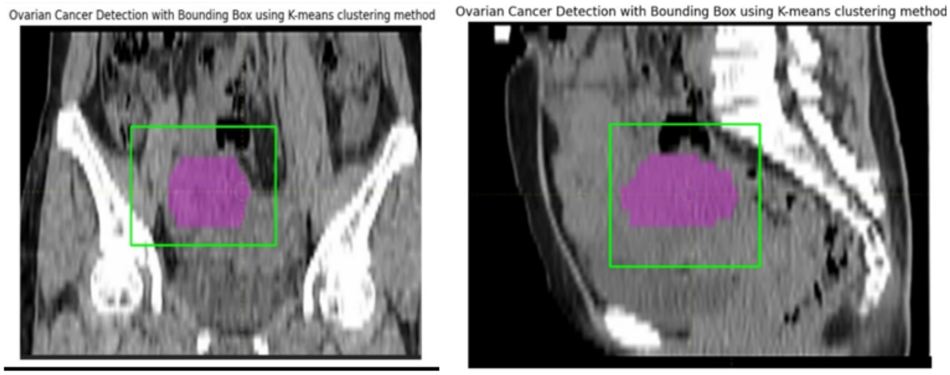

Fig 6. Detection and visual representation of Ovarian Cancer

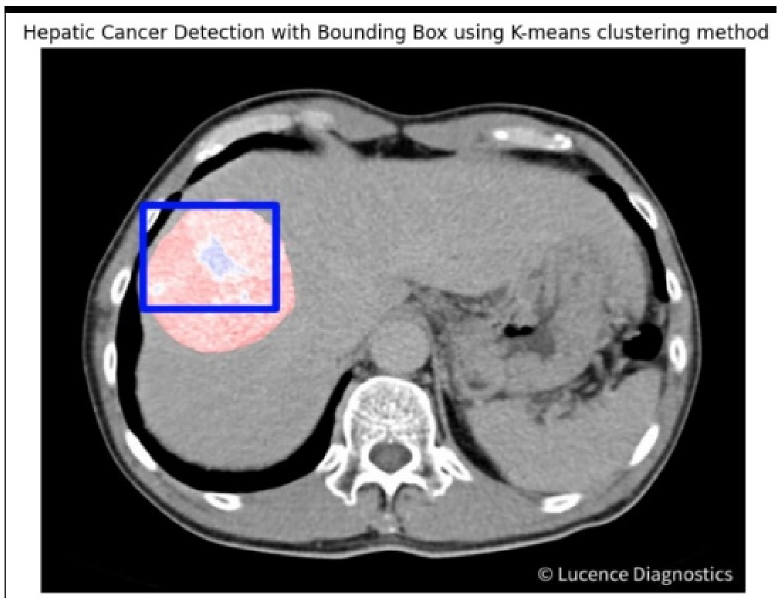

Fig 7. Hepatic Cancer detection with bounding box using K-means clustering

3.4 Accuracy:

The accuracy report as shown in Table 2 clearly indicates that the approach using support vector machine has outperformed Logistic regression and has achieved an accuracy of 86.3% or 0.863 which is higher than 85.1%[12] and 85.3%[13]. While the Logistic regression approach has achieved a precision of 0.82, recall of 0.82, and F1-score of 0.82 which is relatively higher than 0.80[13], 0.73[13] and 0.763[13] respectively, it has achieved a slightly lower accuracy in comparison. It is evident that Support vector machine is the best Machine Learning approach and algorithm for brain tumor detection application. The Machine Learning Based computer Vision technique combines both the process of classification, (through Support Vector Classification and Logistic Regression) and then uses bounding box to visually highlight the tumor affected area.

This research study exhibits an augmented and a refined method for brain tumour detection, doubling down on earlier research that used Machine learning (ML) classification algorithms to help identify brain tumours and their classification based on their varied forms – Glioma, Meningioma, and Pituitary tumours. The algorithms provide clear detections alongside a accuracy value of 86.3 %, highlighting the first-rate performance of Support Vector Machine (SVM) over Logistic Regression, which has triumphed over existing record accuracies of 85.1 % and 85.3 % of former studies[13]. The above[4] has also exhibited promising results in detection hepatic and ovarian tumours. Furthermore, the current work offers a thorough and understandable method of diagnosis by combining Machine Learning (ML) based classifiers with computer vision techniques, specializing in usage of bounding boxes to aid in visual detection of the tumour affected areas. Such a versatile advancement

Table 2. Accuracy report for support vector classifier and Logistic Regression Algorithm

SUPPORT VECTOR CLASSIFIER					
Tumor type	**Precision**	**Recall**	**F1-score**	**Accuracy (current work)**	**Accuracy (previous work)**
No Tumor	0.95	0.74	0.83	0.863 or 86.3%	0.851 [13] or 85.1%
Pituitary Tumor	0.97	0.84	0.90		
Glioma Tumor	0.77	0.97	0.85		
Meningioma Tumor	0.88	0.84	0.86		
Macro Avg	**0.89**	**0.85**	**0.86**		
Weighted Avg	**0.88**	**0.86**	**0.86**		
LOGISTSIC REGRESSION					
Tumor type	**Precision**	**Recall**	**F1-score**	**Accuracy (current work)**	**Accuracy (previous work)**
No Tumor	0.85	0.74	0.79	0.82 or 82%	0.846 [13] or 84.6%
Pituitary Tumor	0.86	0.88	0.87		
Glioma Tumor	0.80	0.84	0.82		
Meningioma Tumor	0.79	0.78	0.78		
Macro Avg	**0.82**	**0.81**	**0.81**		
Weighted Avg	**0.82**	**0.82**	**0.82**		

increases the lucidity of diagnostic healthcare and its usefulness in healthcare and patient safety domains.

Discussion and Analysis:

Table 3. Comparative analysis of works demonstrated for Brain Tumor Classification

CURRENT WORK	
Method	**Accuracy**
Support Vector Classifier	0.863
Logistic Regression	0.820
PREVIOUS LITERATURE WORK	
Naïve Bayes (Binary Classification)	0.796 [13]
K-Nearest Neighbors	0.770 [13]
CURRENT WORK	
Method	**Accuracy**
Support Vector Classifier	0.863
Logistic Regression	0.820
PREVIOUS LITERATURE WORK	
Naïve Bayes (Binary Classification)	0.796 [13]
K-Nearest Neighbors	0.770 [13]

As shown in Table 3, our proposed approach for multi-class classification significantly outperforms existing methods reported in the literature[13]. The Support Vector Classifier (SVC) achieved an accuracy of 86.3%, while Logistic Regression followed with 82.0%. In comparison, previous studies reported lower accuracies, with Naïve Bayes achieving 79.6% and K-Nearest Neighbors (KNN) at 77.0%. These findings highlight the improved capability of our models particularly SVC in effectively distinguishing between the four classes: no tumor, glioma, meningioma, and pituitary tumors.

A notable advancement in our methodology lies in the integration of Computer Vision techniques for the precise identification of abnormal regions associated with Hepatic and Ovarian cancers. This represents a novel contribution within the scope of existing literature. Furthermore, the use of the K-Means Clustering algorithm in conjunction with Computer Vision and OpenCV has significantly enhanced the localization and segmentation of affected areas, offering a more optimized and accurate diagnostic algorithm.

4 Conclusion

Computer vision-based healthcare automation has prevailed and revolutionized data analysis and storage in healthcare. The problems addressed is mainly to improve analysis, classification, and visualization of healthcare data to identify and highlight tumor affected areas in the field of medical imaging. While existing solutions use basic machine learning algorithms, K-means clustering, and Computer Vision techniques, they often lack precision needed for optimal results. The proposed model combines ML and Computer Vision, achieving an accuracy of 86.3% which with a Support Vector Classifier (SVC) which is 1.2% higher than previous models. The proposed model also aims in Logistic Regression (LR), an uncommon method. This advancement not only improves accuracy and efficiency but also ensures patient data security providing a more reliable and secure solution for medical imaging in healthcare.

Acknowledgment

This paper has been presented in "International Conference on Applied Mathematics and Advanced Data Analytics for Industry 5.0 (ICAMADA-2024)" held during 25th to 27th April 2024 at VNR VJIET, in collaboration with APTSMS and CCOE. The authors express their sincere gratitude to the guest editors for their tireless efforts and dedication by means of comments, editing and overseeing the manuscripts to bring in this final form.

The APC is deferred partially by Indian Society for Education and Environment.

This research article was supported by B V Raju Institute of Technology, Narsapur, Medak, Telangana 502313.

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