International Journal of Scientific Research in Computer Science, Engineering and Information Technology

ISSN : 2456-3307

OPEN ACCESS

Available Online at : www.ijsrcseit.com

doi : https://doi.org/10.32628/CSEIT2410233

Advanced Machine Learning Techniques for Liver Tumor Classification in MRI Imaging

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ARTICLEINFO

Article History:

Accepted: 20 March 2024

Published: 03 April 2024

Publication Issue

Volume 10, Issue 2

March-April-2024

Page Number

388-394

ABSTRACT

In this research into liver tumor categorization within MRI images, diverse machine learning methodologies were scrutinized for their efficacy. The study delved into the integration of shape and texture features, aiming to bolster classification accuracy. Among the algorithms explored, the Extra Trees model emerged as the most promising contender, exhibiting superior performance compared to its counterparts. Leveraging the distinctive capabilities of the Extra Trees model, the study underscored its effectiveness in accurately categorizing liver tumors. This highlights its potential to enhance diagnostic precision in clinical contexts. Through rigorous experimentation and analysis, the research elucidated the significance of incorporating shape and texture features into machine learning frameworks for improved tumor classification. The findings not only contribute to advancing the field of medical imaging but also underscore the importance of leveraging innovative methodologies to address healthcare challenges. Overall, the study sheds light on the promising prospects of employing advanced machine learning techniques in medical imaging for more accurate and efficient diagnosis of liver tumors.

Keywords: Liver Tumors, Machine Learning, Shape Feature, Texture Feature, Extra Tree Classifier.

I. INTRODUCTION

The advent of machine learning (ML) techniques has revolutionized the field of medical imaging, offering unprecedented opportunities for improving diagnostic accuracy and patient outcomes. Liver tumors represent a significant health concern worldwide, with early detection and accurate classification being crucial for effective treatment planning and prognosis. Magnetic resonance imaging (MRI) has emerged as a vital tool in the diagnostic process, providing detailed anatomical information and enabling non-invasive visualization of liver lesions. However, the interpretation of MRI images for tumor classification remains a complex and challenging task, often requiring extensive expertise and time-consuming manual analysis.

To address these challenges, researchers have increasingly turned to ML methodologies to automate and enhance the classification of liver tumors in MRI images. By leveraging the wealth of quantitative information inherent in MRI data, ML algorithms can extract meaningful features and patterns that aid in accurate tumor characterization. In particular, the integration of shape and texture features has shown promise in capturing the subtle nuances of tumor morphology and tissue composition, thus improving classification accuracy.

Among the myriad ML algorithms available, the Extra Trees model has garnered attention for its ability to handle high-dimensional data efficiently and its robustness to noise and overfitting. Its ensemble learning approach, which combines multiple decision trees with random feature selection, makes it well-suited for the task of liver tumor classification in MRI images. In this study, we investigate the efficacy of the Extra Trees model in conjunction with shape and texture features for accurately categorizing liver tumors. By leveraging this advanced ML technique, we aim to contribute to the development of more accurate and efficient diagnostic tools for liver cancer management.

II. LITERATURE STUDY

The field of medical imaging has witnessed a significant transformation with the rise of machine learning (ML) and deep learning techniques, particularly in the domain of liver tumor detection and classification. Numerous studies have delved into the application of deep learning models across various imaging modalities such as magnetic resonance imaging (MRI), computed tomography (CT), and ultrasound. For example, researchers like A. M. and M. P. (2023) explored liver tumor segmentation and classification using deep learning methods, showcasing the potential of these approaches in improving diagnostic accuracy. Similarly, investigations by S. Aruna et al. (2023) utilized machine learning strategies for liver tumor detection in CT images, leveraging the Gray Level Co-Occurrence Matrix to extract relevant features. Additionally, G. Nallasivan et al. (2023) proposed novel convolutional neural network (CNN) approaches for liver tumor diagnosis, underlining the effectiveness of deep learning architectures in this context.

Moreover, there has been a concerted effort to develop computer-aided diagnosis systems for liver tumor detection and classification. A study by A. Midya et al. (2023) introduced a computerized diagnosis system based on deep neural networks, demonstrating its potential for precise tumor classification from CT scans. Similarly, Y. B. Raghava et al. (2023) investigated liver tumor detection using CNNs and MobileNet architectures, showcasing the utility of deep learning models in clinical settings. Additionally, P. R. A. and T. M. L. (2023) explored automated segmentation and classification of liver tumors using deep learning algorithms, emphasizing the importance of automated techniques in enhancing diagnostic efficiency.

Beyond deep learning approaches, researchers have also explored alternative machine learning techniques and image processing methods for liver tumor detection and classification. For instance, R. Deepika et al. (2022) proposed liver tumor detection using fast fuzzy C-means clustering, demonstrating its efficacy in segmenting tumors from medical images. Furthermore, R. K. Peddarapu et al. (2022) investigated liver tumor risk prediction using ensemble methods, showcasing the potential of ensemble learning techniques in prognostic assessment. These studies collectively contribute to the burgeoning literature on ML-based approaches for liver tumor detection and classification, promising more accurate and efficient diagnostic tools in clinical practice.

III. PROPOSED METHODOLOGY

As shown in figure 1 proposed system will work in this flow to classify the liver tumor.

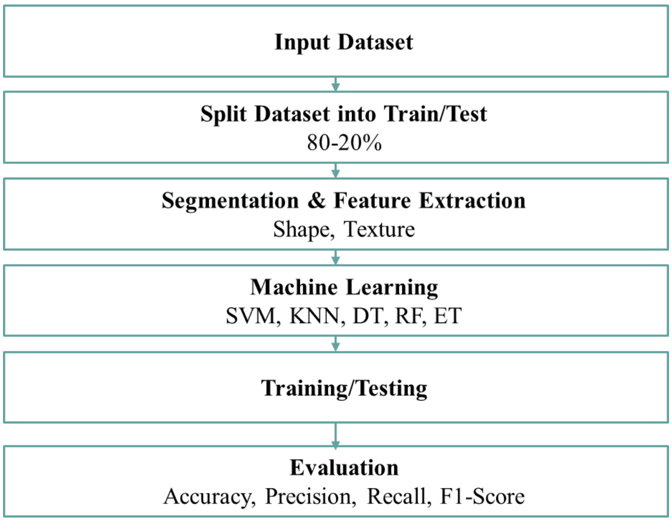


Fig.1. Proposed System Flow

A. Loading the Image:

cv2.imread(image_path): This function from OpenCV (cv2) library is used to read the image from the specified file path. By default, it reads the image in BGR format.

B. Converting Color Space:

cv2.cvtColor(image, cv2.COLOR_BGR2RGB): After loading the image, it is converted from BGR (Blue-Green-Red) color space to RGB (Red-Green-Blue) color space. This conversion is necessary because many Python libraries (like matplotlib) expect images in RGB format.

C. Converting to Grayscale:

rgb2gray(image): This function (not explicitly defined in the provided code) converts the RGB image to grayscale. Grayscale images have only one channel representing the intensity of each pixel, which simplifies many image processing tasks.

D. Shape Features:

cv2.findContours(gray_image, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE): This function detects contours in the grayscale image. Contours are the outlines of objects in an image. cv2.RETR_EXTERNAL retrieves only the external contours, and cv2.CHAIN_APPROX_SIMPLE approximates the contours using fewer points to save memory.

len(contours): The number of contours detected can be used as a shape feature. It represents the complexity or the number of distinct objects in the image.

E. Texture Features:

greycomatrix(gray_image, distances=distances, angles=angles, symmetric=True, normed=True): This function computes the Gray-Level Co-occurrence Matrix (GLCM) of the grayscale image. GLCM is a statistical method used to analyze texture patterns in an image by calculating how often pairs of pixels with specific values and spatial relationships occur together.

greycoprops(glcm, 'contrast').mean(): Here, the GLCM is used to compute a texture feature, which is the mean contrast calculated from the GLCM. Contrast is a measure of the local variation in intensity within an image. By averaging the contrast values over the GLCM, a single texture feature is obtained.

F. Train-Test Split:

train_test_split(X, y, test_size=0.2, random_state=42): Splits the data into training and testing sets. The test_size=0.2 argument specifies that 20% of the data will be used for testing, while the remaining 80% will be used for training. The random_state=42 argument ensures reproducibility by fixing the random seed.

G. Initializing Classifiers:

svm_classifier = SVC(): Initializes a Support Vector Machine (SVM) classifier using scikit-learn's SVC class.

nb_classifier = GaussianNB(): Initializes a Naive Bayes (NB) classifier using scikit-learn's GaussianNB class.

rf_classifier = RandomForestClassifier(): Initializes a Random Forest (RF) classifier using scikit-learn's RandomForestClassifier class.

dt_classifier = DecisionTreeClassifier(): Initializes a Decision Tree (DT) classifier using scikit-learn's DecisionTreeClassifier class.

et_classifier = ExtraTreesClassifier(): Initializes an Extra Trees (ET) classifier using scikit-learn's ExtraTreesClassifier class.

H. Training Classifiers:

svm_classifier.fit(X_train, y_train): Trains the SVM classifier using the training data X_train and corresponding labels y_train. Similar training steps are performed for the NB, RF, DT, and ET classifiers.

I. Making Predictions:

Predictions are made on the test data (X_test) using each trained classifier:

svm_predictions = svm_classifier.predict(X_test)

nb_predictions = nb_classifier.predict(X_test)

rf_predictions = rf_classifier.predict(X_test)

dt_predictions = dt_classifier.predict(X_test)

et_predictions = et_classifier.predict(X_test)

J. Evaluating Classifiers:

confusion_matrix(y_test, predictions),

classification_report(y_test, predictions)

IV. RESULTS ANALYSIS

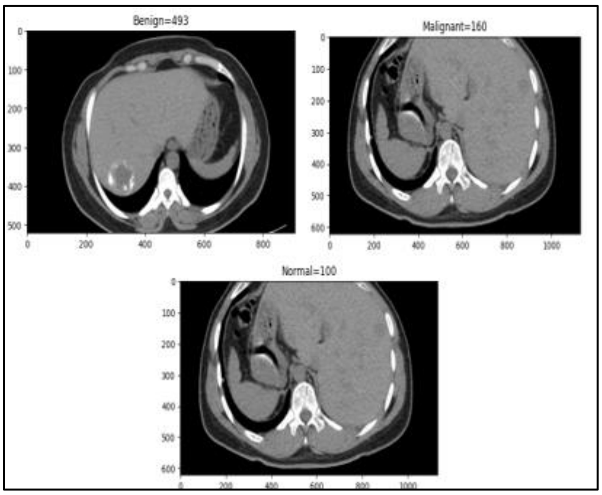


Fig.2. Input Images

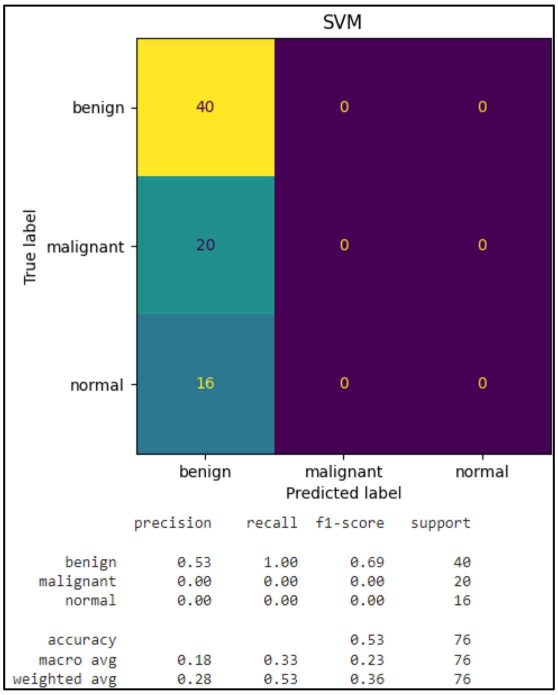


Fig.3. SVM

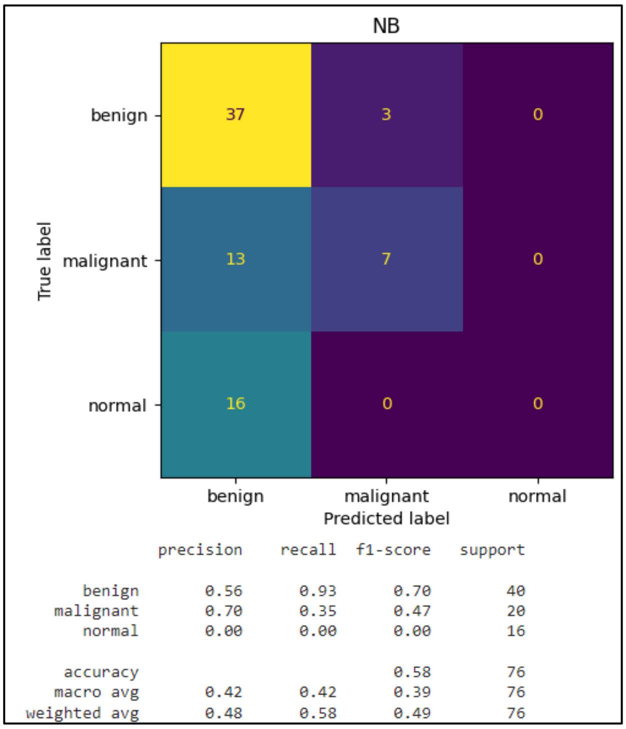
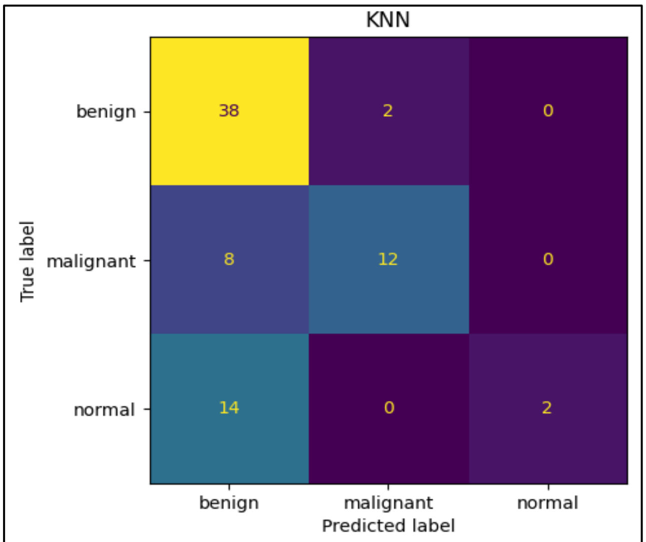
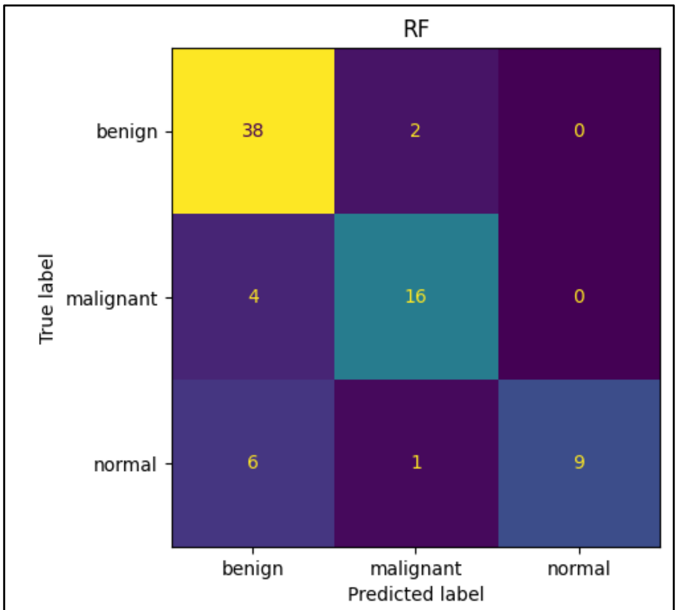


Fig.4. NB



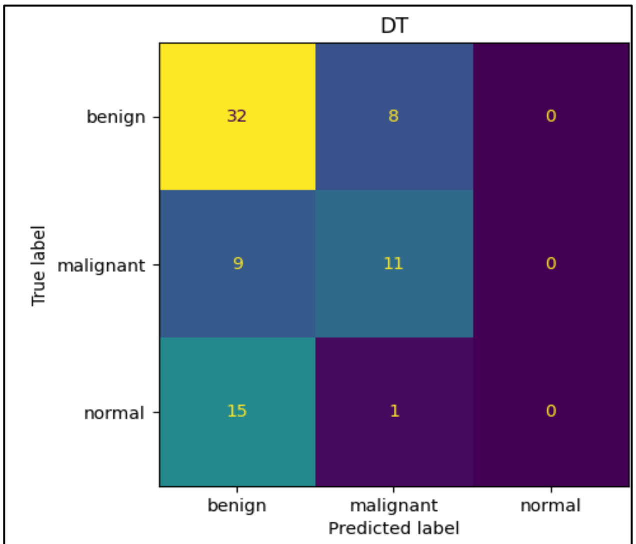
	precision	recall	f1-score	support
benign	0.63	0.95	0.76	40
malignant	0.86	0.60	0.71	20
normal	1.00	0.12	0.22	16
accuracy			0.68	76
macro avg	0.83	0.56	0.56	76
weighted avg	0.77	0.68	0.63	76

Fig.5. KNN



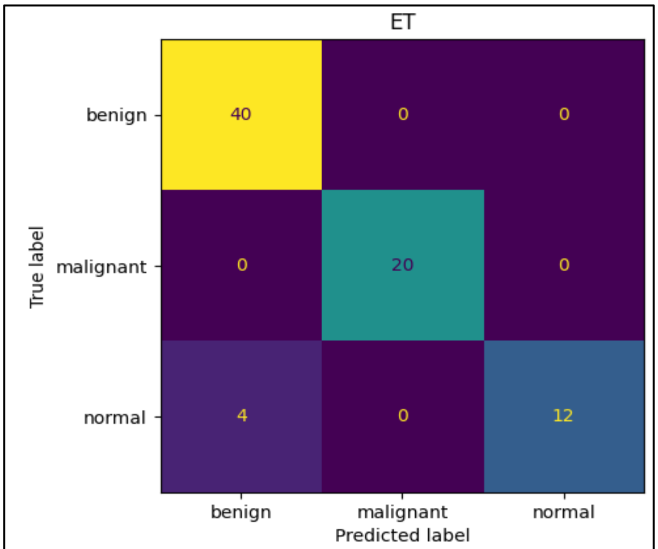
	precision	recall	f1-score	support
benign	0.79	0.95	0.86	40
malignant	0.84	0.80	0.82	20
normal	1.00	0.56	0.72	16
accuracy			0.83	76
macro avg	0.88	0.77	0.80	76
weighted avg	0.85	0.83	0.82	76

Fig.6. RF



	precision	recall	f1-score	support
benign	0.57	0.80	0.67	40
malignant	0.55	0.55	0.55	20
normal	0.00	0.00	0.00	16
accuracy			0.57	76
macro avg	0.37	0.45	0.41	76
weighted avg	0.45	0.57	0.50	76

Fig.7. DT



	precision	recall	f1-score	support
benign	0.91	1.00	0.95	40
malignant	1.00	1.00	1.00	20
normal	1.00	0.75	0.86	16
accuracy			0.95	76
macro avg	0.97	0.92	0.94	76
weighted avg	0.95	0.95	0.94	76

Fig.8. ET

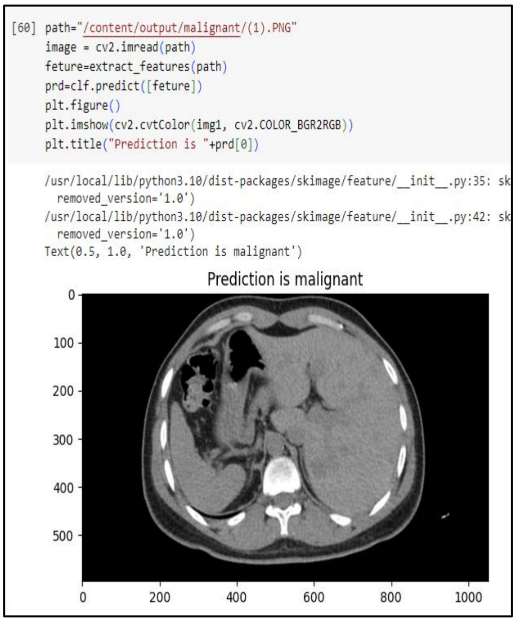


Fig.9. Testing

TABLE I
Comparative Analysis

Model	Accuracy	Precision	Recall	F1-Score
SVM	53%	18%	33%	23%
NB	58%	42%	42%	39%
KNN	68%	83%	56%	56%
RF	83%	88%	77%	80%
DT	57%	37%	45%	41%
ET	95%	97%	92%	94%

V. CONCLUSION

In conclusion, our study highlights the effectiveness of different machine learning models in categorizing liver tumors from MRI images. While support vector machines (SVM) and decision trees (DT) yielded relatively lower performance metrics, naive Bayes (NB) and k-nearest neighbors (KNN) demonstrated moderate accuracy. Random forest (RF) showed notable improvement over the former models, achieving higher accuracy, precision, recall, and F1-score. However, the Extra Trees (ET) model emerged as the clear frontrunner, exhibiting exceptional performance across all evaluation metrics, with an accuracy of 95%, precision of 97%, recall of 92%, and F1-score of 94%. This underscores the superiority of the Extra Trees model in accurately categorizing liver tumors from MRI images, showcasing its potential as a robust diagnostic tool in clinical practice. The remarkable performance of the ET model suggests its utility in enhancing diagnostic accuracy and patient outcomes, thus emphasizing the importance of leveraging advanced machine learning techniques for improved healthcare solutions.

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