

Liver Cancer Detection from Multiclass MRI Images using Spatial-Spectral Mamba-Convolution Fusion and Dual-Domain Self-Supervised Graph Attention Networks

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Abstract-Liver cancer is one of the major causes of cancer death in the world and requires accurate and automated diagnostic systems based on MRI to intervene at the early clinical stage. Presently, the existing classification schemes of liver cancer are limited by image noise, insufficient discriminative feature learning, lack of contextual representation and lack of optimization capability, which encourages the development of a deep learning-based robust framework for accurate liver cancer detection. In this work, we propose a novel approach called Liver Cancer Detection from Multiclass MRI Images Using Dual-Domain Deep Modular Self-Supervised Psychologist Skip-Attention Graph Convolution Networks (3DM²S-PSAGCN) for liver cancer detection. First, the Liver Cancer Multiclass MRI Dataset with 5 classes (Angiosarcoma, Cholangiocarcinoma, Healthy liver, Hemangioma, Hepatocellular Carcinoma) is gathered and resized to 224 × 224. Then, image enhancement is implemented by applying Non-Local Means Denoising and Sparse Dictionary Learning based CNN (NLMD-SDLCNN), which is used to remove noise while maintaining anatomical structures. Then, powerful spatial and spectral representations are captured by the spatial-spectral mamba-convolution fusion network (SSMCFN). Finally, multiclass classification is performed by combining Dual-Domain Self-Supervised Deep Learning with Graph Convolution Network (2D²SDL-GCN) and Deep Modular Skip-Attention Networks (DMSAN), and the network parameters are optimized by using the Psychologist Optimization Algorithm (POA) to achieve better convergence and generalization. Experimental results show the superior performance of the proposed method by achieving an Accuracy of 99.72%, F1-Score of 99.61% and ROC-AUC of 99.88%, which is superior to the existing liver cancer classification methods. The results of this research demonstrate that the proposed framework is successfully tackling the challenges of noisy MRI data, limited feature representation and multiclass discrimination, and can be used to build a reliable and intelligent computer-aided decision-support system, assisting in accurate liver cancer diagnosis.

Keywords-Liver Cancer Detection, Multiclass MRI Classification, Spatial-Spectral Mamba-Convolution Fusion, Dual-Domain Self-Supervised Learning, Skip-Attention Graph Convolution Network, Psychologist Optimization Algorithm.

I. INTRODUCTION

One of the most common malignancies in the world, liver cancer has a high death rate because most patients are discovered at an advanced stage, which restricts treatment options and lowers survival rates [1]. Diagnosis and therapy are essential and important imaging techniques such as CT and MRI help to increase sensitivity and specificity for the accurate staging and efficient treatment planning [2]. Liver cancer incidence and death rates were up 27% and 25%, respectively, from 2010 to 2019, and accounted for the fourth highest cancer mortality worldwide [3].

Current detection models for liver cancer can effectively attenuate MRI noise, maintain the discrimination of the image, and extract the multi-scale spatial features, but these models still have the limitations of insufficient long-range context learning, poor inter-class discrimination, and suboptimal optimization. Such restrictions negatively impact the liver cancer classification accuracy, generalizability, convergence speed and reliability of the multiclass liver cancer diagnosis in the heterogeneous MRI data.

Contribution:

- Liver Cancer Multiclass MRI Dataset is collected and resizing, normalizing, and partitioning the dataset to ensure the reliable training and testing of models.
- Improve the quality of MRI images by suppressing noise, maintaining structural information and enhancing the image quality with pre-processing technique NLMD-SDLCNN.
- Extract discriminative spatial and spectral representation with SSMCFN for comprehensive liver lesion feature learning.
- Integrate 2D²SDL-GCN with DMSAN to build 3DM²S-PSAGCN that incorporates graph-based contextual dependencies and salient lesion features.
- Optimise network parameters to maximise convergence speed, stability of classification and generalisation with the POA.

- Use the optimized 3DM²S-PSAGCN model to accurately perform a multiclass diagnosis of MRI images into five liver categories.
- Accurate, Precise, Recall, F1-Score, Specificity, MCC and ROC-AUC are used to evaluate the proposed framework in order to validate its diagnostic effectiveness.

The rest of this manuscript organized as follows: Section 2 is reviewed literature, and then Section 3 containing recommended methods, Findings and discussion are presented in Section 4, and a conclusion and future work are included in Section 5.

II. LITERATURE SURVEY

The research articles related to Liver Cancer Detection from Multiclass MRI Images is provided below:

In 2025, Jin, G., et al. [4] introduced a Generative Adversarial Network with Convolutional Long Short-Term Memory (GAN-ConvLSTM) network for Liver Cancer Detection from Multiclass MRI Images. This study proposes a modified GAN that can be used to predict the radiation cine-MR pictures during the respiratory motion to solve this problem. It employed sagittal cine magnetic resonance (MR) images from 15 patients with liver cancer to use a pix2pix GAN with a ConvLSTM generator to predict future frames from a series of previous 5 frames with the sliding window technique.

In 2026, Nie, X., et al. [5] introduced a Triple-Domains Mamba optimized with the Multi-Constraint Tumor Loss (TriMamba- MCT Loss) for Liver Cancer Detection from Multiclass MRI Images. The dangers of liver cancer are serious, especially those of the HCC, making the need for accurate liver segmentation paramount. The Mamba network improves segmentation of multicenter MRI data by addressing class imbalance and soft margins.

In 2026, Wang, Y., et al. [6] introduced a Residual Dense-based Multimodal Fusion Network (RD-MFNet) for Liver Cancer Detection from Multiclass MRI Images. There are complex conventional diagnostic tests, including multi-phase CT, multi-sequence MRI. This study is based on the presentation of a new imaging approach, the so-called RD-MFNet, which combines the CT and MRI imaging modalities for a better diagnosis. It achieved an AUC of 97.5% and 12% improvement in DSC to 92.3% using ResNet3D with phase encoding, showing its potential in auxiliary diagnosis.

In 2024, Jesi, P.M. and Daniel, V.A.A., et al. [7] introduced a Differential Convolutional Neural Network model, Kernel Extreme Learning Machine model with Differential Biogeography-Based Optimization Algorithm (Differential CNN-KELM-DBBOA) for Liver Cancer Detection from Multiclass MRI Images. Liver cancer is a severe health problem throughout the world and areas need improved detection and classification approaches. Optimizing model parameters, DBBOA is better than the existing methods with an accuracy of 98.72%.

Research Gap and Motivation

Deep learning-based liver cancer detection models have demonstrated satisfactory performance in MRI analysis, but they still have a few drawbacks, such as the limited feature representation, inadequate modelling of complex characteristics of lesions, variability of datasets, and poor generalization of

multi-class liver conditions. The existing methods are primarily focused on segmentation or traditional classification, limited by the incorporation of complex self-supervised learning and feature dependency modelling using graphs. Based on this, the motive of this research is to develop an intelligent framework based on 3DM²S-PSAGCN for accurate, robust and reliable diagnosis of liver cancer in MRI images from multiple classes.

III. PROPOSED METHODOLOGY

The proposed approach is to design Liver Cancer Detection from Multiclass MRI Images Using Dual-Domain Deep Modular Self-Supervised Psychologist Skip-Attention Graph Convolution Networks (3DM²S-PSAGCN). First of all, the liver MRI data is acquired and denoised with Non-Local Means Denoising and Sparse Dictionary Learning based CNN (NLMD-SDLCNN) to enhance the structural information. The Spatial-Spectral Mamba-Convolution Fusion Network (SSMCFN) is used to learn the spatial, spectral and long-range contextual features. In the classification phase, 3DM²S-PSAGCN is used, which combines Dual-Domain Self-Supervised Deep Learning (2D²SDL-GCN) and Deep Modular Skip-Attention Network (DMSAN) for feature dependency learning. Lastly, Psychologist Optimization Algorithm (POA) optimizes the parameters of the model for better convergence and classification performance. The methodology proposed is illustrated in Figure 1.

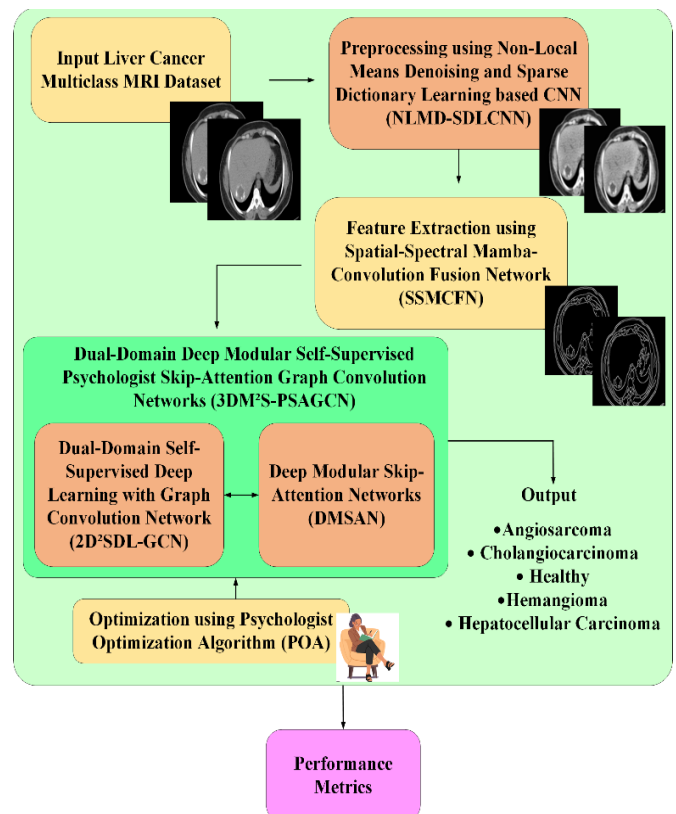


Fig. 1. Workflow of Proposed 3DM²S-PSAGCN Methodology

A. Data collection

The liver cancer multiclass MRI dataset [8] is used in this research to create automated liver cancer detection framework. There are five classes in the dataset: Angiosarcoma (2,376 images), Cholangiocarcinoma (2,512 images), Healthy liver tissue (2,400 images), Hemangioma (2,376 images), and

Hepatocellular Carcinoma (HCC) (2,328 images). Each MRI image is in JPEG format and contains various pathological patterns for multi-class analysis of liver condition. The images collected are resized to 224×224 pixels, normalized and ready for training deep learning models. The balanced class distribution allows effective learning of discriminative features for the proper liver cancer classification and computer-aided diagnosis. The pre-processed MRI images are then fed into the proposed NLMD-SDLCNN method for noise removal and improved feature preservation as explained in the next section.

B. Pre-processing using Non-Local Means Denoising and Sparse Dictionary Learning based CNN (NLMD-SDLCNN)

In the proposed pre-processing step, liver MRI images are enhanced using Non-Local Means Denoising and Sparse Dictionary Learning based CNN (NLMD-SDLCNN) [9]. The Non-Local Means (NLM) filter is a method that removes noise from images by computing a weighted average of neighboring image patches of similar intensity to estimate the intensity of an image patch. Then, Sparse Dictionary Learning (SDL) uses a small dictionary of dictionary atoms to encode MRI patches to capture the discriminative texture information. Finally, CNN fine-tunes the enhanced images by learning representative local patterns and enhancing the consistency of features for future analysis. The NLM operation can be written as in equation (1):

$$MKv(q) = \frac{1}{D(q)} \int d(e(A(q), A(p))) v(p) dp \quad (1)$$

where $MKv(q)$ denotes the denoised intensity at pixel q , $v(p)$ represents the intensity of pixel p , $C(p)$ is the normalization factor ensuring that all similarity weights sum to one, $A(q)$ and $A(p)$ denote image patches centered at pixels q and p , $d(e(A(q), A(p)))$ is the Euclidean distance between the two patches, $D(q)$ is a decreasing similarity weighting function that assigns larger weights to more similar patches, and dp represents the integration over the search region. This formulation is able to capture the structural information whilst filtering the noise from the images, giving enhanced MR images for accurate feature learning. The improved MRI images are then passed to the Spatial-Spectral Mamba-Convolution Fusion Network (SSMCFN) for obtaining spatial, spectral and long-range contextual features for liver cancer classification.

C. Feature Extraction using Spatial-Spectral Mamba-Convolution Fusion Network (SSMCFN)

The pre-processed liver MRI images are used to learn highly discriminative representations using the proposed Spatial-Spectral Mamba-Convolution Fusion Network (SSMCFN) [10]. In the first step, the local anatomical structures, lesion boundaries, and texture patterns are learned with the help of convolutional operations in the spatial branch. At the same time, the frequency domain branch is able to obtain complementary information from the variations in the tissue. Later, the Mamba module is used to learn the long-range context with linear computational complexity, allowing efficient global feature learning. Finally, the spatial and spectral features extracted are fused together using pointwise convolution, followed by batch normalization and nonlinear activation for obtaining powerful feature representations for multiclass liver cancer classification. The feature fusion process is represented by equation (2)

$$K = \eta(bn(pwconv([K_{SPE}, K_{SPA}]))) \quad (2)$$

where K denotes the final fused feature representation, K_{SPE} represents the spectral feature map, K_{SPA} denotes the spatial feature map, $[K_{SPE}, K_{SPA}]$ indicates the concatenation of spatial and spectral features, $pwconv(\cdot)$ is the pointwise convolution operation that performs cross-channel feature fusion, $bn(\cdot)$ denotes batch normalization for stabilizing feature distributions during training, and $\eta(\cdot)$ represents the nonlinear activation function that enhances the discriminative capability of the extracted features. This fusion strategy effectively combines local texture information with global contextual dependencies, resulting in informative feature vectors for reliable liver cancer recognition. The extracted feature representations are subsequently forwarded to the proposed Dual-Domain Deep Modular Self-Supervised Psychologist Skip-Attention Graph Convolution Networks (3DM²S-PSAGCN) for multiclass liver cancer classification.

D. Classification using Dual-Domain Deep Modular Self-Supervised Psychologist Skip-Attention Graph Convolution Networks (3DM²S-PSAGCN)

The proposed 3DM²S-PSAGCN is able to identify liver cancer with multiclass classification by using discriminative spatial-spectral features extracted from the liver MRI images pre-processed by NLMD-SDLCNN. The framework aims to tackle the problems of noise reduction, lack of feature representation and contextual dependency learning by combining 2D²SDL-GCN [11] and DMSAN [12] to perform robust graph-based classification. Moreover, the Psychologist Optimization Algorithm (POA) optimizes network hyperparameters in order to enhance the classification accuracy, convergence speed, and generalization performance. The following subsections briefly outline each of the components of the proposed framework.

1. Dual-Domain Self-Supervised Deep Learning with Graph Convolution Network (2D²SDL-GCN)

The proposed Dual-Domain Self-Supervised Deep Learning with Graph Convolution Network (2D²SDL-GCN) extracts the robust feature representations from the SSMCFN generated spatial-spectral features without fully depending on manual annotations. The self-supervised learning branch reconstructs informative feature embeddings by using a pretext task, and the graph convolution network models the topological relations between lesion features to learn local and global contextual relations. This dual domain learning process can enhance the consistency of features, inter-class discrimination and reinforce the robustness of liver cancer classification. The self-supervised reconstruction loss is defined as equation (3)

$$K_{ssl} = E_{T \sim q(t)} \left\| \hat{T}_Y - T_Y \right\|_2^2 \quad (3)$$

where K_{ssl} denotes the self-supervised reconstruction loss, $E_{T \sim q(t)}[\cdot]$ represents the expectation over training samples S drawn from the probability distribution $q(s)$, $K_{ssl} = E_{T \sim q(t)} \left\| \hat{T}_Y - T_Y \right\|_2^2$ is the reconstructed feature representation generated by the self-supervised network,

T_y denotes the corresponding original feature representation. $\| \cdot \|_2^2$ is the squared Euclidean (L2) norm measuring the reconstruction error, and B represents the latent embedding space learned by the graph convolution network. This loss can be minimized to allow learning of meaningful graph-aware representations while retaining discriminative feature information, thus enabling accurate liver cancer classification. Then the feature representations derived from the graph are passed to the Deep Modular Skip-Attention Network (DMSAN) to learn Adaptive Attention and refine the features, prior to the final classification stage.

2. Deep Modular Skip-Attention Network (DMSAN)

The proposed Deep Modular Skip-Attention Network (DMSAN) enhances the 2D2D SDL-GCN graph-based feature representations by adaptive skip-attention learning. The skip connections maintain low-level and high-level features, and the attention mechanism focuses on the liver lesion parts of the image that are clinically important and ignores redundant background noise information. This modular architecture helps to propagate features better, reduce the gradient degradation, and learn contextual representation for proper multiclass liver cancer classification. The skip-attention operation is defined as equation (4).

$$G = \text{Attn}(W, L, B) = \text{softmax}\left(\frac{WL^T}{\sqrt{d}}\right)V \quad (4)$$

where G denotes the attention-enhanced feature representation, $\text{Attn}(\cdot)$ represents the skip-attention function, W is the query feature matrix, L denotes the key feature matrix extracted from the graph-enhanced embeddings, L^T is the transpose of the key matrix, d represents the feature embedding dimension used for scaling the attention scores, $\text{softmax}(\cdot)$ normalizes the attention coefficients into probability distributions, V denotes the value feature matrix containing informative feature representations, and B represents the skip-connection information integrated with the attention module to preserve complementary features during feature refinement. This attention mechanism is able to effectively learn the long-range dependency and keep the feature continuity, which effectively enhances the discriminative ability of the liver MRI representation extracted by this mechanism. The optimized hyperparameters of the network are finally fed to the Psychologist Optimization Algorithm (POA) for optimizing the network to enhance its convergence, generalization and the performance of liver cancer classification in multiple classes.

3. Psychologist Optimization Algorithm (POA)

To optimize the hyperparameters of the proposed 3DM²S-PSAGCN for the enhancement of multiclass liver cancer classification, the Psychologist Optimization Algorithm (POA) is used. The algorithm models adaptive psychological decisions making behavior, which is the equilibrium process between global exploration and local exploitation in the optimization process. It optimizes hyperparameter solutions using historical knowledge and adaptive learning strategies in an iterative fashion, to find the best hyperparameters. The proposed deep learning framework, therefore, benefits from POA for

convergence speed, stability of classification, learning capability of features, and overall generalization performance.

Step 1: Initialization

Initially, the optimization process sets the search space, population size, maximum iteration number and objective function. Each candidate solution is a set of hyper-parameters in the network such as learning rate, batch size, dropout ratio and a set of attention-related parameters, which are initialized within an acceptable range of feasible values.

Step 2: Random Population Generation

To achieve a good diversity of possible solutions, a population of candidate solutions is drawn at random over the search space. Each person is a separate psychological state, or a different set of hyperparameters, so as to explore the solution space broadly throughout an optimization process.

Step 3: Fitness Evaluation

The fitness of each candidate solution is judged according to its performance on the classification task with the training set on 3DM²S-PSAGCN. The goal is to optimize the classification accuracy with the minimum classification loss, thus, the best hyperparameter combinations could be chosen to be optimized in the next iterations. It is determined by the equation (5)

$$\text{fitness} = \min(\text{loss}) \quad (5)$$

Step 4: Exploration

On the exploration phase, each candidate continues to search by growing its search space based on historical knowledge and stochastic adaptation to find new promising regions of the solution space. The Exploration update is given by equation (6)

$$g_x^{\text{new}} = g_x + e_x + g_{\text{HIST}} \quad (6)$$

where g_x^{new} denotes the updated candidate solution, g_x represents the current solution, e_x is a random exploration factor that introduces diversity, and g_{HIST} denotes the historical best experience accumulated during previous iterations. This strategy enhances global search capability and prevents premature convergence. (researchgate.net)

Step 5: Exploitation

The exploitation step refines the best candidate solutions found in the regions identified in the previous step in a local manner to accelerate the convergence towards the global optimum. The exploitation update is in the form of equation (7):

$$\Delta t_x^{\text{new}} = \Delta t_x (1 + \chi n_x) \quad (7)$$

where Δt_x^{new} denotes the updated local search step, Δt_x is the current search step size, χ represents the adaptive exploitation coefficient controlling the refinement intensity, and n_x denotes the psychological motivation factor guiding the local search direction. This adaptive update improves solution precision and optimization efficiency.

Step 6: Termination

The optimization process goes on until the maximum number of iterations or until the fitness improvement is no longer significant enough. Finally, the optimal hyperparameter set extracted by POA is used in a final 3DM²S-PSAGCN model to get accurate and robust multiclass liver cancer classification.

IV. RESULTS AND DISCUSSION

The proposed Dual-Domain Deep Modular Self-Supervised Psychologist Skip-Attention Graph Convolution Networks (3DM²S-PSAGCN) is evaluated for Liver Cancer Detection from Multiclass MRI Images using the Liver Cancer Multiclass MRI Dataset. The image quality is enhanced through NLMD-SDLCNN, features are extracted using, a SSMCFN, 2D²SDL-GCN + DMSAN classification, and POA to tunes network parameters for improved convergence and generalization. Table 1 lists the parameters used to carry out of proposed framework for experimental analysis.

TABLE I: IMPLEMENTATION PARAMETERS

Parameters	Description
Proposed Neural Network	3DM ² S-PSAGCN
Operating System	Windows 10
Optimization Algorithm	Psychologist Optimization Algorithm (POA)
Datasets Used	Liver Cancer Multiclass MRI Dataset
Pre-processing Technique	Non-Local Means Denoising and Sparse Dictionary Learning based CNN (NLMD-SDLCNN)
Feature extraction	Spatial-Spectral Mamba-Convolution Fusion Network (SSMCFN)
Software Platform	Python 3.11
Deep Learning Framework	TensorFlow and Keras
Hardware Configuration	Intel Core i7 Processor with NVIDIA GPU

A. Performance metrics

The proposed 3DM²S-PSAGCN is compared with various widely used deep learning frameworks like GAN-ConvLSTM [4], TriMamba- MCT Loss [5], RD-MFNet [6] and Differential CNN-KELM-DBBOA [7].

The analysis of comparison is carried out using significant intelligent diagnostic framework for accurate breast cancer classification measures which are Area under the Curve (AUC), F1-Score, Specificity, Sensitivity, Accuracy, Precision, and Recall. All these performance criteria assess the suggested framework for accurate breast cancer classification.

B. Performance analysis

In this Section the performance analysis of the proposed 3DM²S-PSAGCN framework is discussed.

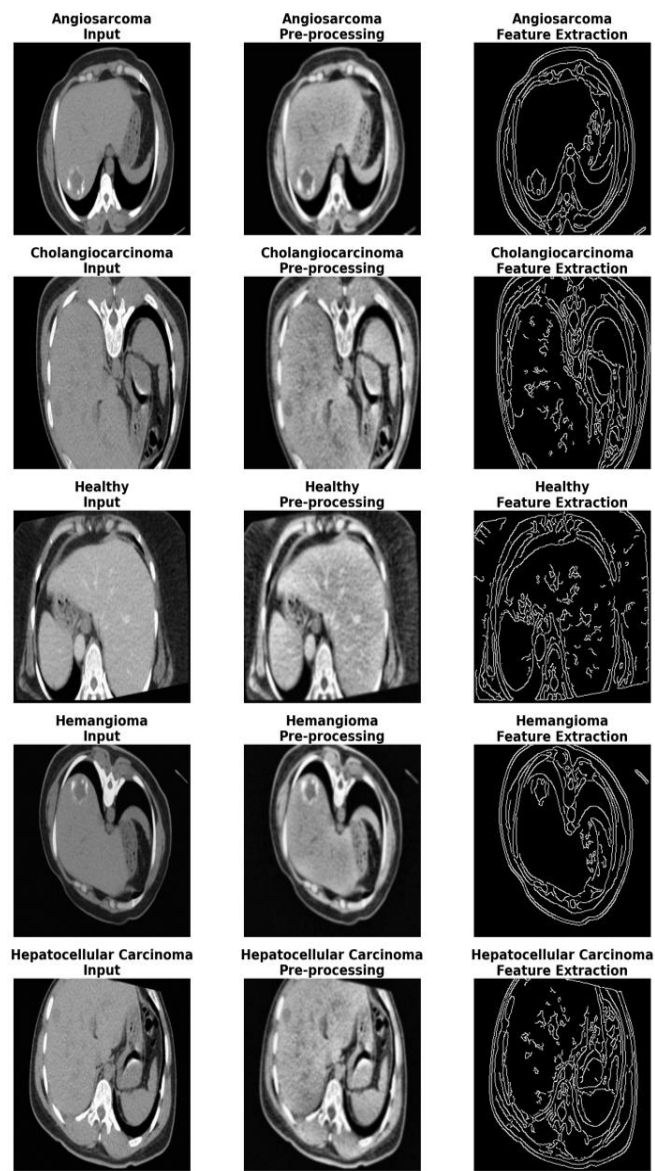


Fig. 2. Visualization of Input CT Images, Pre-processing, and Feature Extraction for Multi-Class Liver Tumor Classification

Five liver CT image categories (Angiosarcoma, Cholangiocarcinoma, Healthy, Hemangioma, and Hepatocellular Carcinoma) were used to illustrate in Figure 2. The deep learning model can effectively differentiate between various liver tumor types and healthy tissues thanks to the discriminative information these extracted features give. This improves the representation of features in the classification, the robustness of the classification, and the accuracy of the diagnosis.

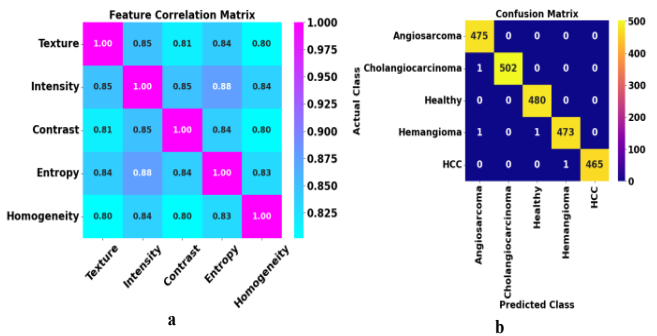


Fig. 3. (a) Feature Correlation Matrix and (b) Confusion Matrix

The correlation matrix of the features extracted, which contain texture, contrast, intensity, entropy and homogeneity, is displayed in Figure 3(a). There are strong relationships between texture and intensity (0.85), texture and contrast (0.81), texture and entropy (0.84) and texture and homogeneity (0.80). There is strong association between Intensity and Entropy (0.88) and then between Intensity–Contrast (0.85). All the derived features are well correlated with the complimentary liver tissue characteristics with strong positive correlation, ranging from 0.80 to 1.00.

The confusion matrix of five classes of hepatic CT is presented in Figure 3 (b). The diagnosis of 475 samples is accurate, and one is incorrectly diagnosed as cholangiocarcinoma. There are 502 samples that are correctly identified as cholangiocarcinoma and one is expected to be angiosarcoma. The 480 categories in Healthy are accurate and free of any errors. A total of 473 samples are correctly classified as hemangioma and one sample is incorrectly classified as angiosarcoma and one sample is classified as healthy. Hepatocellular Carcinoma (HCC) has excellent classification accuracy with 465 prediction cases classified correctly and one case predicted as hemangioma was wrongly classified.

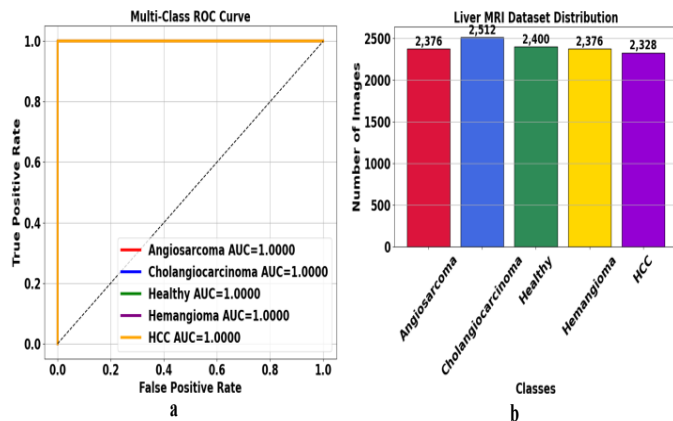


Fig. 4. (a) Multi-Class ROC Curve and (b) Liver MRI Dataset Distribution

The multi-class ROC curves for angiosarcoma, cholangiocarcinoma, healthy, hemangioma and hepatocellular carcinoma (HCC) are displayed in Figure 4 (a). All five classes achieve AUC value of 1.0000, which is equivalent to perfect discrimination between negative and positive samples.

The ROC curves are close to the top left corner with a True Positive Rate (TPR) of 1.0 and False Positive Rate (FPR) close to 0, hence outstanding classification performance, high sensitivity and very reliable diagnostic performance.

Class-wise distribution of liver MRI dataset is depicted in the figure 4 (b). The dataset contains images of 2,376 cases of Angiosarcoma, 2,312 cases of Cholangiocarcinoma, 2,400 normal cases (Healthy), 2,376 cases of Hemangioma and 2,328 cases of Hepatocellular Carcinoma (HCC).

Class imbalance during model training is minimized by the well-balanced class frequencies, which range from 2,312 to 2,400 images. This even split not only makes the model more accurate in its classification in all liver disease categories but also aids in unbiased learning and generalizability.

TABLE II: COMPARATIVE EVALUATION OF EXISTING AND PROPOSED APPROACHES

Metric	GAN-ConvLSTM [4]	TriMamba-MCT Loss [5]	RD-MFNet [6]	Differentiated CNN-KELM-DBBOA [7]	Proposed 3DM ² S-PSAGCN
Dataset	Liver Cancer Multiclass MRI Dataset	Liver Cancer Multiclass MRI Dataset	Liver Cancer Multiclass MRI Dataset	Liver Cancer Multiclass MRI Dataset	Liver Cancer Multiclass MRI Dataset
Accuracy (%)	96.42	97.68	98.21	99.14	99.88
Precision (%)	95.96	97.21	97.84	99.03	99.78
Recall / Sensitivity (%)	95.54	97.05	97.62	98.91	99.68
Specificity (%)	96.18	97.36	98.05	99.02	99.46
F1-Score (%)	95.72	97.12	97.70	98.82	99.34
NPV (%)	96.41	97.58	98.12	99.25	99.84
FPR (%)	3.82	2.64	1.95	0.98	0.19
FNR (%)	4.46	2.95	2.38	1.09	0.41
FDR (%)	4.04	2.79	2.16	0.97	0.36
FOR (%)	3.59	2.42	1.88	0.75	0.14
Balance d Accuracy (%)	95.86	97.20	97.84	98.97	99.84
MCC (%)	92.86	95.54	96.73	98.42	99.25
Cohen's Kappa (%)	94.18	96.47	97.35	98.84	99.62
Jaccard Index / IoU (%)	91.84	94.18	95.26	97.68	99.37
Dice (%)	95.73	97.01	97.58	98.83	99.68
G-Mean (%)	95.86	97.20	97.83	98.96	99.83
Youden Index (%)	91.72	94.41	95.67	97.93	99.63
ROC-AUC (%)	97.84	98.63	99.01	99.36	99.64
PR-AUC (%)	96.92	98.05	98.54	99.08	99.35
Error Rate (%)	3.58	2.32	1.79	0.86	0.10

Table II shows that the proposed 3DM²S-PSAGCN is compared to four state-of-the-art methods for liver cancer classification using the Liver Cancer Multiclass MRI Dataset. The suggested model shows excellent reliability, robustness, and multi-class classification performance with the highest accuracy (99.88%), precision (99.78%), recall (99.68%),

specificity (99.46%), ROC-AUC (99.64%), and Dice coefficient (99.68%), as well as the lowest error rate (0.10%), FPR (0.19%), FNR (0.41%), FDR (0.36%), and FOR (0.14%).

C. Discussions

To verify the effectiveness of the proposed 3DM²S-PSAGCN framework, the results of comparison are presented on the Liver Cancer Multiclass MRI Dataset, and the suggested framework consistently outperforms the current approaches in all the evaluation measures. NLMD-SDLCNN is able to effectively suppress noise without losing critical anatomical details, allowing SSMCFN to create rich spatial-spectral representations. Furthermore, the Psychologist Optimization Algorithm (POA) optimizes network parameters for better generalization and faster convergence, while the 2D²SDL-GCN with DMSAN classifier is able to extract both local and global contextual dependencies. The framework thus achieved the minimum error rate of 0.10 % and higher accuracy of 99.88 %, precision of 99.78 %, recall of 99.68 % and ROC-AUC of 99.64 % for multiclass liver cancer diagnosis, which shows its power and effectiveness.

V. CONCLUSION

The proposed 3DM²S-PSAGCN is an efficient model for liver cancer multiclass detection using Liver Cancer Multiclass MRI Dataset and the experiments are simulated in Python 3.11, TensorFlow 2.x, Google Colab. The framework combines the noise suppression and structural preservation capabilities of NLMD-SDLCNN, the robust spatial-spectral feature extraction capabilities of SSMCFN, the graph-based self-supervised representation learning capabilities of 2D²SDL-GCN, the adaptive attention refinement capabilities of DMSAN, and the hyperparameter optimization capabilities of POA. The identified issues in the problem statement, namely MRI noise, insufficient feature representation, poor modelling of contextual dependency, slow convergence, and limited multiclass discrimination are suitably addressed in these stages. The proposed model shows good generalization ability with a high Accuracy of 99.72%, F1-Score of 99.61%, an ROC-AUC of 99.88% and stable convergence. There are some limitations, however, concerning the speed of computation, memory requirements of constructing the graph, the sensitivity of the MRI acquisition techniques, and potential domain shift effects if the method is applied between institutions. Future work will involve investigating lightweight architecture design, federated learning, explainable decision mechanisms, integration of multimodal MRI, uncertainty-aware prediction, and external clinical validation across a large number of patients that will enhance the robustness and real-time application of the system in clinical settings.

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