

Artificial Intelligence-Based Ensemble Approach for Medical Decision Support Systems on Lung and Colon Cancer Diagnosis Using Histopathological Images

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Abstract—Cancer accounts for a vast death rate owing to its aggressiveness, massive latent metastasis, and heterogeneity (which causes resistance against chemotherapy). Lung and colon cancers (LCC) are one of the most dominant varieties of cancer all over the world, which occurs in both females and males. Prompt and precise analysis of these cancers can greatly enhance the excellence of treatment and the survival rate of cancer patients. Histopathological classification is vital in leading effectual treatment programs for these cancers. The usage of machine learning (ML) and deep learning (DL) techniques has the latent to haste up cancer analysis procedures by permitting scholars to inspect huge patient datasets affordably and rapidly. This study presents a novel Artificial Intelligence-Based Ensemble Approaches for Lung and Colon Cancer Diagnosis (AIBEA-LCCD) algorithm. The main purpose of the AIBEA-LCCD is to offer an efficient framework for the precise and reliable detection of LCC using histopathological images (HIs). In the beginning, the AIBEA-LCCD performs image pre-processing utilizing the adaptive bilateral filtering (ABF) method to increase the image quality by noise reduction whereas maintaining critical edges and details. Next, the CapsNet method has been applied for the extraction of features to capture spatial hierarchies and relationships among the features. Finally, an ensemble of three models, namely, deep gate recurrent unit (DGRU), Siamese neural network (SNN), and denoising autoencoder (DAE) models are deployed for the LCC diagnosis process. To establish a good classification result of the AIBEA-LCCD technique, a huge sort of simulations occur on the benchmark image database. The widespread comparative outcomes certified the improvement of the AIBEA-LCCD over other current techniques.

Keywords—Lung and colon cancer; artificial intelligence; histopathological images; feature extraction; Siamese neural network

I. INTRODUCTION

Lung and Colon cancers pose considerable problems in global health, regarding either their occurrence or impact [1]. Lung cancer is usually identified as cancer around the globe [2]. It is frequently connected to higher mortality rates due to its limited treatment options and aggressive nature, specifically while identified at complex phases [3].

Early diagnosis plays an essential role in enhancing patient consequences through several health conditions, mainly in tumors. Timely recognition allows to accomplish appropriate and rapid treatment approaches, frequently resulting in increased chances and better prognosis of effective treatment [4]. For cancers like colon and lung cancer, early diagnosis enables interference at a phase while the disease might still be minimally or localized invasive, thus providing more treatment options and possibly curative results. Additionally, early detection can decrease the necessity for aggressive treatment and reduce combined mortality and morbidity rates.

Symptoms that serve as early indicators of tumors are indirect cancer markers. Common symptoms such as muscle pain, cough, fatigue, and others, often overlap with several types of illnesses [5]. The major device that exposes the occurrence of cancer is clinical imaging gadgets. Radiographic imaging models like computed tomography (CT), histopathological imaging, mammography, ultrasound, positron emission tomography (PET), and magnetic resonance imaging (MRI) can often leveraged for cancer recognition [6]. Particularly, HIs encompassing phenotypic data are essential for the assessment and analysis of cancer illnesses in specialists. Thus, time-consuming and necessitates a robust focus [7]. Furthermore, case detection is much more complex in early diagnosis cases because, at the beginning of illness, these indications are very difficult and vague to identify.

Machine Learning (ML) is a division of Artificial Intelligence (AI), which permits machines to acquire information and perform specific tasks based on their exposure to it, eliminating the need for explicit programming [8]. Deep learning (DL) techniques are cutting-edge to permit machines to manage larger-dimensional data like multi-dimensional videos and images [9]. Currently, the technical development in the field of clinical imaging and image processing has offered numerous effectual and profitable computer-assisted diagnostic approaches. This model removes a usual set of handcrafted attributes from trained classifiers and histology imageries through extracted features for classifying the cancerous cells [10].

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This paper introduces a new Artificial Intelligence-Based Ensemble Approaches for LCC Diagnosis (AIBEA-LCCD) methodology. In the beginning, the AIBEA-LCCD approach performs image pre-processing utilizing the adaptive bilateral filtering (ABF) model to improve image qualities by reducing noise. Next, the CapsNet method executed for the extraction of the feature. Finally, an ensemble of three models such as deep gate recurrent unit (DGRU), siamese neural network (SNN), and denoising autoencoder (DAE) models are deployed for the LCC diagnosis process. To establish a good classification result of the AIBEA-LCCD model, a huge sort of simulations occurs on the benchmark image dataset.

II. LITERATURE WORKS

Gulsoy and Kablan [11] developed FocalNeXt, an innovative ConvNeXt-augmented FocalNet structure particularly intended for automatic LC recognition. In [12], a DL method is projected. This paper employs histopathological images for colon cancer identification. The developed method presented an innovative model employing ViT and novel ViT version termed Swin Transformer. This method attains higher precision as malignant or benign by applying an adapted version of the Swin Transformer model. Gowthamy and Ramesh [13] developed a comprehensive model to improve colon cancer classification and detection. These images endure pre-processing to increase quality, succeeded by augmentation to improve the size of the dataset and develop model generalization. A DL-based transformer model is intended for effective feature extractors and improving classification by integrating a convolutional neural network (CNN). A cross-transformation model takes longer-range dependency between fields, and an AM allocates weights to emphasize vital attributes. To boost classification precision, a Siamese network differentiates colon cancer tissue classes depending on possibilities.

The authors [14] established HI for the early detection of LCC through the ensemble DL (HIELCC-EDL) technique. Additionally, the hyper-parameter choice of the CA-ResNet50 technique is implemented utilizing the TSO model. Eventually, the LCC recognition is obtained by utilizing the ensemble of 3 classifiers competitive neural networks, LSTM, and extreme learning machine (ELM). Jayaraj et al. [15] introduce a novel structure that depends on the Improved Neural Network and Optimization Technique (INNOT) for recognizing lung disease, comprising Covid-19 and pneumonia in X-rays of individual patient's chests. This technique enhanced the X-ray's picture quality over the median filtering application and then histogram equalization deliberating the quality of image degenerated through the process. Fuzzy particle swarm optimization (FPSO) is utilized previously to apply an Artificial Neural Network for classification to choose the finest probable aspects. Razmjouei et al. [16] developed a metaheuristic-driven dual-phase ensemble DL technique. The analysis of colon and lung cancers is endeavored utilizing multiple unique indicators by diverse variants of deep CNN (DCNN) in model constructions and feature extractors, employing the power of multiple ML models for final classification. In the subsequent stage, the feature selection optimization is accompanied by employing a metaheuristic model depending on the Electric Eel Foraging Optimization (EEFO).

Elhassan et al. [17] examined to improve lung cancer detection by applying a grouping of dual learning methods: a CNN for classification and the YOLO-v8 structure. CNN automatically learns to remove hierarchical features from raw image data. YOLO-v8 integrates a multi-scale feature extractor. Additionally, over the usage of pioneering data augmentation approaches, like Deep Convolutional GSN (DCGAN), the recommended method can manage the problem of confined data and improve the capability. Turk et al. [18] introduced an automated diagnosis method. This method aimed to timely recognition over image pre-processing with a 2-D GF, whereas sustaining simpleness to reduce computation desires and runtime. Moreover, the investigation delivers the necessity for safety levels in the technique by utilizing CAM for explanatory purposes.

III. PROPOSED METHODOLOGY

In this manuscript, we have introduced an innovative AIBEA-LCCD approach. The major purpose of the AIBEA-LCCD approach is to offer a reliable framework for the precise and reliable diagnosis of LCC using HIs. To accomplish that, the AIBEA-LCCD system has noise reduction, feature extractor, and ensemble classification. Fig. 1 exemplifies the complete procedure of the AIBEA-LCCD system.

A. Noise Reduction: ABF Model

At first, the AIBEA-LCCD approach executes image pre-processing exploiting the ABF to increase the image qualities by reducing noise while maintaining critical edges and details. ABF is a non-linear image smoothing technique, which efficiently decreases the noise while maintaining vital edges in histopathological imaging [19]. In the context of LCC recognition, ABF improves the excellence of microscopic tissue images, which makes it simpler to distinguish cancerous areas from healthy tissues. The filter adjusts to local image features, certifying that fine details like cell boundaries and tumor features are sustained. By enhancing the image clarity, ABF aids more precise feature extraction and classification that is critical for accurate cancer diagnosis. This pre-processing stage plays an essential part in improving the efficiency of AI-based techniques in perceiving and identifying cancer in histopathological imaging.

B. Feature Extraction: CapsNet Model

The CapsNet method has been applied for the extraction of features to capture spatial hierarchies and relationships among the features. CapsNet is proved to be a type of ANN that aims to effectively capture ranked connections by the usage of capsules instead of neurons similar to the key elements of computation [20]. Neurons clusters, which characterize the attributes and probability of a particular feature are called capsules. Diverse attributes of an object are communicated by them, with its direction, presence, location, and form. Additionally, capsules are qualified to comprehend the spatial networks and different locations of input features, which are frequently ignored in conventional NNs. A CapsNet contains different capsule layers, all of which characterize a novel abstraction level. This updated procedure is implemented according to the positioning of their posture variables. It is capable of understanding the relations between various pieces and whole objects, providing more

significance to capsules, which determine a strong relation with capsules these are high-level.

The output of the CapsNet comprises a series of vectors that all vectors associate with a certain class. The intended class was described by vectors, which consist of either the possibility or

pose variables. A marginal loss function is applied to train the CapsNet. The current function stimulates the relevant categories to include long vectors and discourages incorrect types not in possession of long vectors. Additionally, the margin loss function contains a regularization term, which reprimands the current NN to assign greater likelihoods to some types.

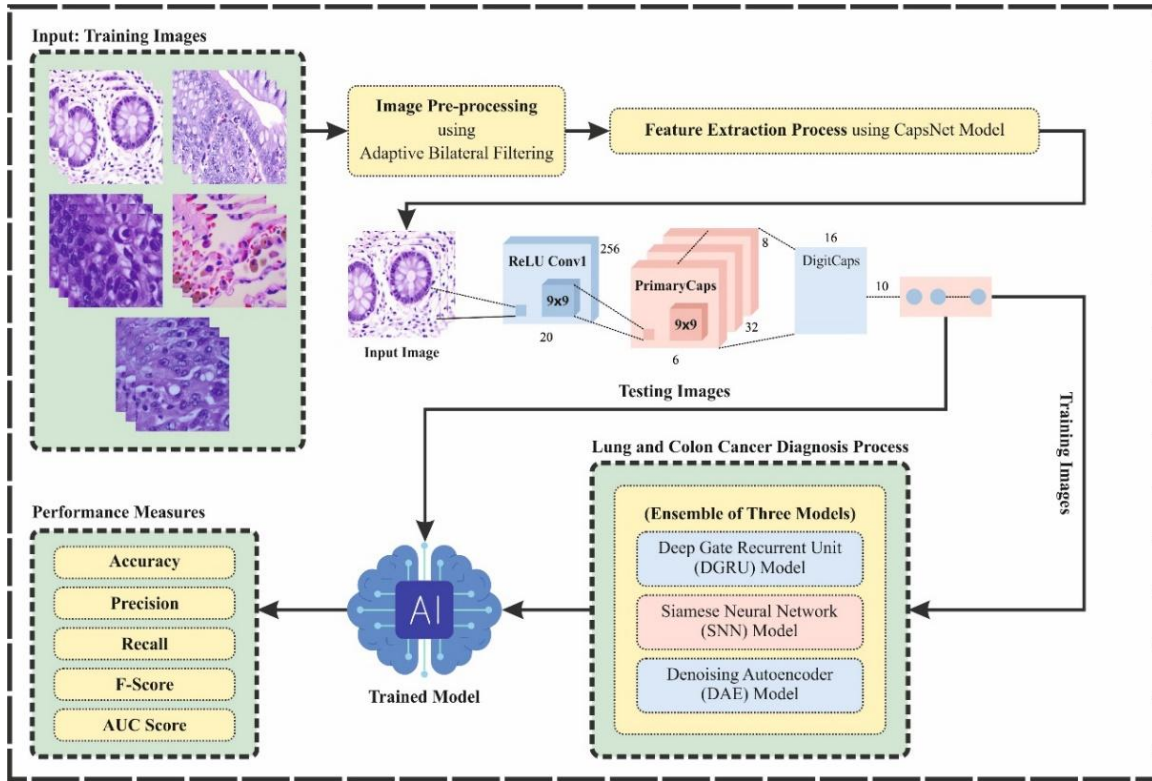


Fig. 1. Overall process of AIBEA-LCCD algorithm.

All capsules present inside the primary layers contain an activity vector p_j , which characterizes geographical data in the instantiating component of the capsule index, which is established by j . The output vector p_j of low-grade capsule j is implemented inside the following layer $l+1$, which is applied to every capsules. Candidate i attains the input p_i and calculates output by the value of the weighted matrix $Y_{j,i}$ inside layer $l+1$. The final vector of prediction $p_{j,i}$ exemplifies the quantity of the first j that constitutes i .

$$p_{j,i} = Y_{j,i} \times p_j \quad (1)$$

The level of agreement amongst the candidates, with the major feature for predicting the candidate j 's method to candidate i , is established by multiplying the major predicting feature of candidate j by the coupling coefficient. Both candidates are associated it is guaranteed they are aligned. Therefore, the coefficient of coupling increases after the inverse takes place. To evaluate the outcome of the individual squeezing function, the complete amount (Yx_i) is assigned and allocated to the major predicting of candidate i .

$$Yx_i = \sum_{j=1}^N q_{j,i} \hat{p}_{i,j} \quad (2)$$

$$d_i = \frac{\|Yx_i\|^2}{1 + \|Yx_i\|^2} \frac{Zc_j}{\|Ys_i\|} \quad (3)$$

$$q_{j,i} = \frac{\exp(b_{j,i})}{\sum_k \exp(b_{k,i})} \quad (4)$$

Compression is related to the limits and potentiality of an output of the individual to values n in the interval of $(0 - 1)$. The capsule layer d_i transfers to the following layer that shows a similar way to the previous layer. The main level of prediction is proved by qj and generalized to layer $l+1$. During all cycles, the result $\hat{p}_{j,i}$ is attained. Every capsule's vector is considered as the combination of dual values that are numerical.

C. Classification Process: Three Ensemble Approaches

Moreover, an ensemble of three approaches namely DGRU model, SNN technique, and DAE model are deployed for the LCC diagnosis process.

1) *DGRU model*: The DGRU is the recent DL technique appropriate for the time-series processing of data [21]. By stacking numerous layers of GRU, DGRU attains a deep feature extractor and can improve seizure composite time dependencies. RNN is a kind of NN appropriate for handling data sequences. Its important characteristic is to take the

temporal dependences in order through joining data at dissimilar time steps over a HL. GRU is an enhanced RNN, which improves the gradient exploding or vanishing problem by presenting a reset and an update gate. Thus efficiently handling state updates and data transmission. The single GRU method contains an input layer, an output layer, and HL.

$$\begin{cases} z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \\ r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \\ \tilde{h}_t = \tanh(W_h \cdot [r_t h_{t-1}, x_t]) \\ h_t = (1 - z_t) \odot h_{t-1} + \tilde{h}_t \odot z_t \\ y_t = \partial(W_y h_t + b_y) \end{cases} \quad (5)$$

where, z_t and r_t denote the output of the update and reset gate, h_t signifies HL of the present time step, x_t denotes input of present time-step, $\odot$ characterizes point-wise multiplication, σ represents the function of the sigmoid activation, $\tanh$ represents activation function of the hyperbolic tangent, and ∂ means the function of linear activation. Additionally, W_r , W_z , W_y , and W_h relate to the weighting of reset gate, update gate, output layer, and intermediate resultant layer, correspondingly. h_t and $\tilde{h}_t$ represents HL and intermediate HL, individually. Y denotes the output of the model, and B_y signifies output layer bias. DGRU makes a deeper networking architecture by stacking numerous layers of GRU to attain additional composite feature extractors and gain of temporal dependences. The DGRU structure is comprised of numerous GRU layers components stacked together, and the output of all layers performs the input of the following layer.

$$\begin{cases} h_t^1 = GRU(x_t, h_{t-1}^1) \\ h_t^2 = GRU(h_t^1, h_{t-1}^2) \\ \vdots \\ h_t^l = GRU(h_t^{l-1}, h_{t-1}^l) \\ \vdots \\ h_t^L = GRU(h_t^{L-1}, h_{t-1}^L) \end{cases} \quad (6)$$

In which, L refers to layer counts in the DGRU architecture, and h_t^l stands for HL of the l_{th} layer at t_{th} time step. All layers contain the capability to take temporal dependences at various levels that are united to offer a complete understanding of series data. By joining the deep structure and GRU method, DGRU contains the capability to take composite temporal dependences and increase the performance of the model.

2) *SNN classifier*: SNN is a kind of NN structure that contains dual parallel NN sharing similar weights and structures [22]. The term Siamese derives from the concept of binary Siamese twins who are related but manage individually. The SNN is skilled together to pairing input data to compare their identities or for learning relationships among them. It demonstrates substantial strength in some shot learning or single shot learning to resolve image verification as the image-related concerns. There are 2 parallel networks inside the SNN. Every colored bar red and blue might be metaphorically considered as hidden representations attained from distinct but similar NN inside the Siamese structure. The particular aspects in every Siamese network will obtain a diverse portion of data

as input. The shared weight permits the systems to combine to learn a usual data representation.

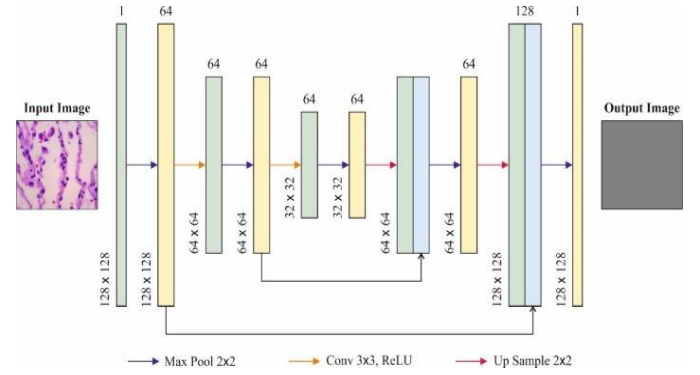


Fig. 2. DAE Architecture.

When diverse kinds of input data originate from several resources and reveal dissimilar models but they occur in certain associations amongst others, the structures and weights of every Siamese network also might be diverse based on hidden aspects from diverse kinds of input data. Regarding this paper, the SNN technique shares a similar structure and weight as either input or similar kind of data, or the LSTM component is accepted to handle dynamics in the industrial data process, deliberated as earlier.

3) *DAE Approach*: The DAE can detect a similar structural overview in the image despite the noisy disruptions that establish its strength in measuring plausible structure [23]. The DAE architecture is derived from an expansion of the important AE method, containing dual modules: an encoding and a decoding. The encoder (E) incorporates the noisy image x_η into its low-dimensional hidden representation $= E_\theta(x_\eta)$, subsequently, the decoder re-establishes the hidden representation reverse into a pixel-based image area $\hat{x} = D_\theta(w) = D_\theta \circ E_\theta(x_\eta)$. This system has been trained to utilize the succeeding loss function:

$$\begin{aligned} \min_{E_\theta, D_\theta} \Delta(x, \hat{x}) &= \frac{1}{n} \sum_{i=1}^n (x_i - \hat{x}_i)^2 \\ &= \frac{1}{n} \sum_{i=1}^n (x_i - D_\theta \circ E_\theta(x_i + \eta))^2 \end{aligned} \quad (7)$$

Whereas n refers to batch size. However reducing the error of reconstruction at training, DAE successively exploits the mutual data amongst the new input x and its hidden model w . Particularly, this model avoids noise corruption amongst x and $\hat{x}$. It permits the latent model w to comprise important data concerning the resource x , although DAE just understands the corrupted input $\hat{x}$. Fig. 2 portrays the architecture of DAE.

IV. EXPERIMENTAL ANALYSIS

The investigational validation of AIBEA-LCCD approach is inspected under the lung and colon cancer HIs dataset [24]. This database encompasses 25000 images in 5 classes as shown in Table I. Fig. 3 indicates the sample images.

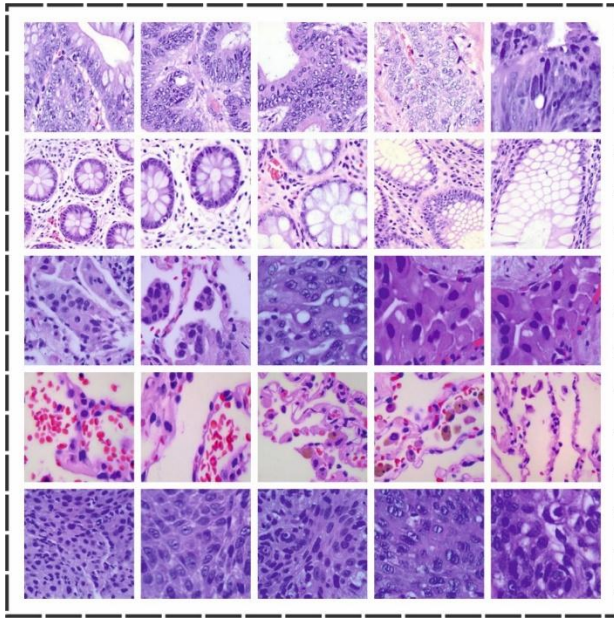


Fig. 3. Sample Images

TABLE I. DATASET DETAILS

Class Labels	Descriptions	No. of Images
“Col-Ad”	“Colon Adenocarcinoma”	“5000”
“Col-Be”	“Colon Benign Tissue”	“5000”
“Lun-Ad”	“Lung Adenocarcinoma”	“5000”
“Lun-Be”	“Lung Benign Tissue”	“5000”
“Lun-SC”	“Lung Squamous Cell Carcinoma”	“5000”
Total No. of Images		25000

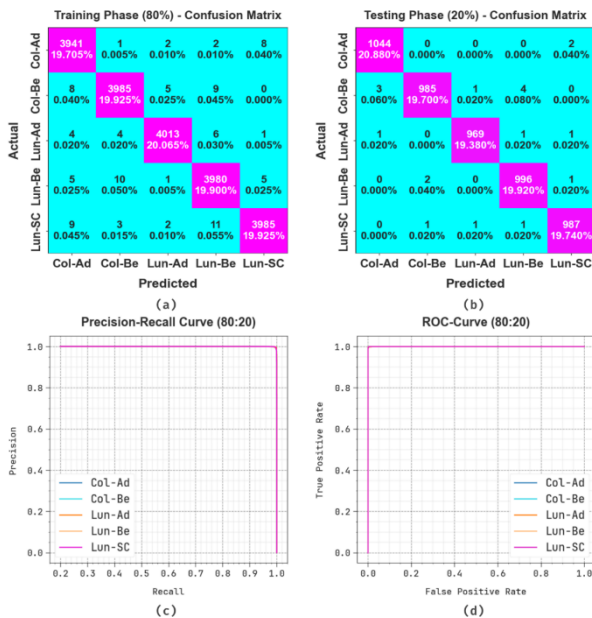


Fig. 4. 80% TRPE and 20% TSPE of (a-b) confusion matrix and (c-d) Curves of PR and ROC.

Fig. 4 defined the classifier results of the AIBEA-LCCD methodology below 80%TRPE and 20%TSPE. Fig. 4a-4b

displays the confusion matrices with proficient recognition of every class. Fig. 4c demonstrates the PR values, demonstrating greater solution across 5 classes. Finally, Fig. 4d shows the ROC results, establishing effective performance with optimum ROC investigation for numerous classes.

Table II and Fig. 5 exposes the classifier results of AIBEA-LCCD algorithm under 80%TRPE and 20%TSPE. The results showed that the AIBEA-LCCD achieved effective recognition of all class labels. Based on 80%TRPE, the AIBEA-LCCD system reaches an average acc [ur] _y of 99.52%, pre [ci] _n of 99.52%, rec [al] _l of 99.52%, F_score of 99.52%, and [AUC] _score of 99.70%. Besides, with 20%TSPE, the AIBEA-LCCD approach delivers an average acc [ur] _y of 99.62%, pre [ci] _n of 99.62%, rec [al] _l of 99.62%, and F_score of 99.62% and [AUC] _score of 99.76%.

TABLE II. CLASSIFIER RESULT OF AIBEA-LCCD APPROACH AT 80%TRPE AND 20%TSPE

Classes	Accur _y	Preci _n	Recal _l	F _{score}	AUC _{score}
TRPE (80%)					
Col-Ad	99.67	99.34	99.67	99.51	99.75
Col-Be	99.45	99.55	99.45	99.50	99.67
Lun-Ad	99.63	99.75	99.63	99.69	99.78
Lun-Be	99.48	99.30	99.48	99.39	99.65
Lun-SC	99.38	99.65	99.38	99.51	99.64
Average	99.52	99.52	99.52	99.52	99.70
TSPE (20%)					
Col-Ad	99.81	99.62	99.81	99.71	99.85
Col-Be	99.19	99.70	99.19	99.44	99.56
Lun-Ad	99.69	99.79	99.69	99.74	99.82
Lun-Be	99.70	99.40	99.70	99.55	99.77
Lun-SC	99.70	99.60	99.70	99.65	99.80
Average	99.62	99.62	99.62	99.62	99.76

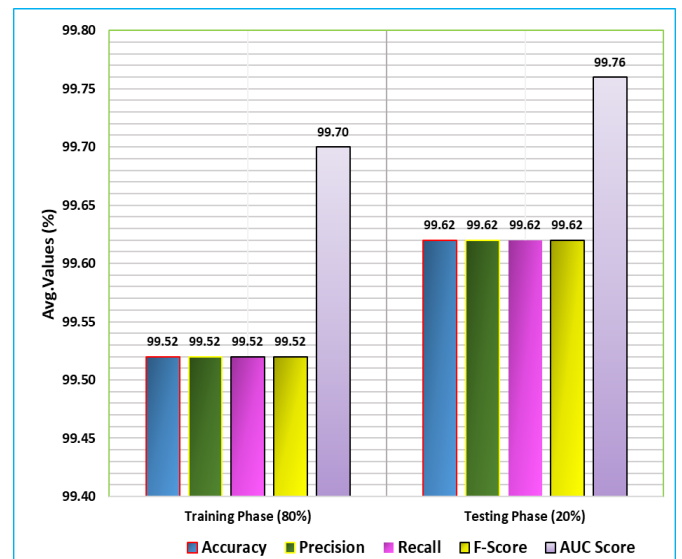


Fig. 5. Average of AIBEA-LCCD system at 80%TRPE and 20%TSPE.

In Fig. 6, the training (TR) acc [ur] _y and validation (VAT) acc [ur] _y of AIBEA-LCCD algorithm under 80% TRPE and 20% TSPE are demonstrated. The acc [ur] _y investigation is evaluated under an interval of 0-25 epochs. The solution highpoints that the TR and VAT acc [ur] _y curve demonstrations rising tendencies that informed the competence of AIBEA-LCCD model with maximal results under multiple iterations. At the same time, the TR and VAT acc [ur] _y remains nearer under the epochs, showing minimal overfitting and demonstrates maximum outcomes of AIBEA-LCCD, assuring constant prediction on hidden instances.

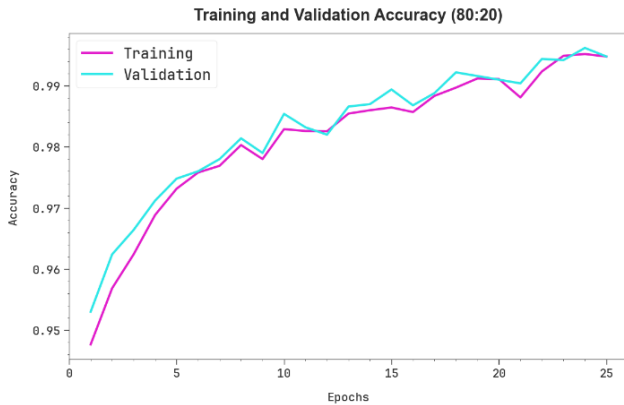


Fig. 6. $Accur_y$ graph of AIBEA-LCCD method with 80%TRPE and 20%TSPE.



Fig. 7. Loss graph of AIBEA-LCCD algorithm with 80%TRPE and 20%TSPE.

In Fig. 7, the TR loss (TRLOS) and VAT loss (VATLOS) curve of AIBEA-LCCD methodology under 80%TRPE and 20%TSPE is demonstrated. The outcomes of loss are considered through 0-25 epochs. It implies that the TRLOS and VATLOS examination represent lessening tendencies, notifying the capability of AIBEA-LCCD balancing a trade-off among data fitting and generality.

Fig. 8 exhibits the classifier outcomes of the AIBEA-LCCD system at 70%TRPE and 30%TSPE. Fig. 8a-8b reveals the confusion matrices with effectual identification of each class. Fig. 8c exhibits the PR curve, suggests greater outcomes over every class. Concurrently, Fig. 8d proves the curve of ROC, representative effective results with maximum ROC study for numerous classes.

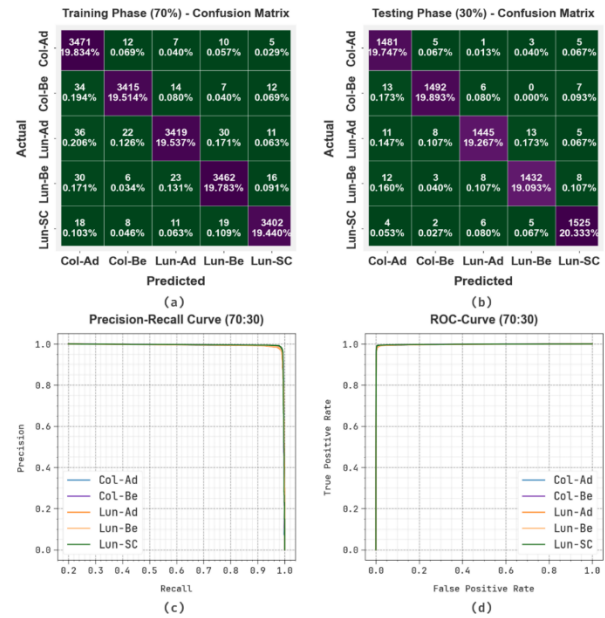


Fig. 8. 70% TRPE and 30% TSPE of (a-b) confusion matrix and (c-d) PR and ROC.

TABLE III. CLASSIFIER RESULTS OF AIBEA-LCCD APPROACH BELOW 70%TRPE AND 30%TSPE

Classes	Accur _y	Preci _n	Recal _l	F _{score}	AUC _{score}
TRPE (70%)					
Col-Ad	99.03	96.71	99.03	97.86	99.09
Col-Be	98.08	98.61	98.08	98.34	98.87
Lun-Ad	97.19	98.42	97.19	97.80	98.40
Lun-Be	97.88	98.13	97.88	98.00	98.70
Lun-SC	98.38	98.72	98.38	98.55	99.03
Average	98.11	98.12	98.11	98.11	98.82
TSPE (30%)					
Col-Ad	99.06	97.37	99.06	98.21	99.20
Col-Be	98.29	98.81	98.29	98.55	98.99
Lun-Ad	97.50	98.57	97.50	98.03	98.58
Lun-Be	97.88	98.55	97.88	98.22	98.77
Lun-SC	98.90	98.39	98.90	98.64	99.24
Average	98.33	98.34	98.33	98.33	98.95

Table III and Fig. 9 indicate the classifier solution of the AIBEA-LCCD under 70%TRPE and 30%TSPE. The performance demonstrated that the AIBEA-LCCD method reached powerful detection of all classes. With 70%TRPE, the AIBEA-LCCD system accomplishes an average $accur_y$ of 98.11%, $preci_n$ of 98.12%, $recal_l$ of 98.11%, F_{score} and 98.11%, and AUC_{score} of 98.82%. Besides, with 30%TSPE, the AIBEA-LCCD algorithm reaches an average $accur_y$ of 98.33%, $preci_n$ of 98.34%, $recal_l$ of 98.33%, F_{score} of 98.33%, and AUC_{score} of 98.95%.

In Fig. 10, the TR $accur_y$ and VAT $accur_y$ analysis of the AIBEA-LCCD approach below 70%TRPE and 30%TSPE is

illustrated. The *accu_r* curve is evaluated with the range of 0-25 epochs. The outcome highpoints that the TR and VAT *accu_r* investigation reveals a growing trend which learned the capability of AIBEA-LCCD with maximum outcomes across many iterations. Next, the TR and VAT *accu_r* remains close under the epochs, indicating lower overfitting and depicts increased results of AIBEA-LCCD system, ensuring dependable prediction on unnoticed samples.

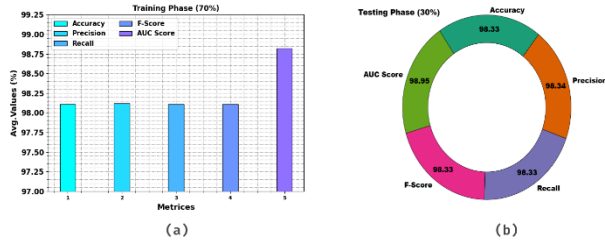


Fig. 9. Average of AIBEA-LCCD methodology with 70%TRPE and 30%TSPE.

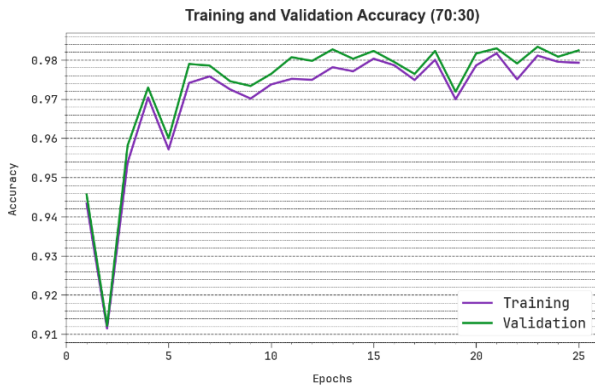


Fig. 10. *Accu_r* curve of AIBEA-LCCD system at 70%TRPE and 30%TSPE.



Fig. 11. Loss analysis of AIBEA-LCCD model at 70%TRPE and 30%TSPE.

In Fig. 11, the TRLOS and VATLOS curve of AIBEA-LCCD on 70%TRPE and 30%TSPE is depicted. The outcome of loss are evaluated through 0-25 epochs. It is indicated that the TRLOS and VATLOS examination illustrate a lessening tendencies, notifies the competence of AIBEA-LCCD algorithm in stabilizing a trade-off among generality and data fitting.

Table IV and Fig. 12 exhibit the comparative results of AIBEA-LCCD with other systems [25-27]. The results show

that the m-SRC, Faster RCNN, RESNET-50, and DL algorithms have attained somewhat closer results. Whereas, the BJCLCD-TSADL, MPADL-LC3, BERTL-HIALCC, and MPADL-LC3 approaches have reached the worst performance. Meanwhile, the proposed AIBEA-LCCD system has gained better outcomes with *accu_r* of 99.62%, *preci_n* of 99.62%, *recal_l* of 99.62%, and *F_{score}* of 99.62%.

TABLE IV. COMPARATIVE OUTCOMES OF AIBEA-LCCD WITH EXISTING CLASSIFIERS

Classifier	<i>Accu_r</i>	<i>Preci_n</i>	<i>Recal_l</i>	<i>F_{score}</i>
AIBEA-LCCD	99.62	99.62	99.62	99.62
BJCLCD- TSADL	99.41	98.38	98.37	98.37
MPADL-LC3	99.33	98.25	98.24	98.25
BERTL-HIALCC	99.28	98.12	98.14	98.14
MPADL-LC3	99.15	98.06	97.27	97.15
m-SRC Method	88.27	85.27	91.85	86.85
Faster RCNN	98.85	96.58	97.70	97.39
RESNET-50 Model	93.70	96.19	97.55	97.01
DL Algorithm	96.40	96.93	96.51	97.15

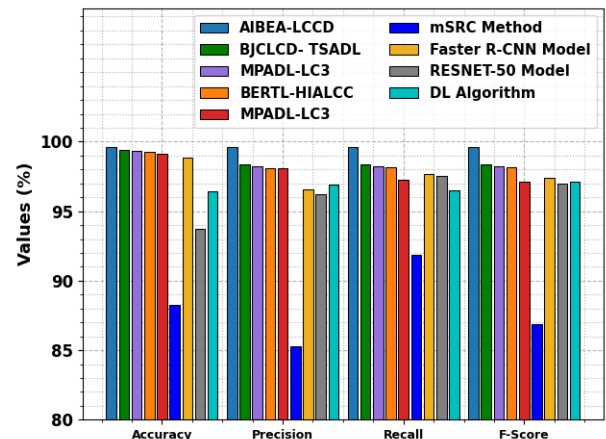


Fig. 12. Comparative results of AIBEA-LCCD system with existing classifiers.

TABLE V. CT RESULTS OF AIBEA-LCCD METHODOLOGY WITH OTHER METHODS

Classifier	Computational Time (sec)
AIBEA-LCCD	7.84
BJCLCD- TSADL	15.34
MPADL-LC3	12.81
BERTL-HIALCC	15.59
MPADL-LC3	16.76
m-SRC Method	10.61
Faster RCNN Model	19.06
RESNET-50 Model	16.19
DL Algorithm	24.39

Table V and Fig. 13 deliver the computational time (CT) result of AIBEA-LCCD with existing classifiers. The table

outcomes imply that the AIBEA-LCCD approach accomplishes a great CT of 7.84sec. Meanwhile, the existing systems such as BJCLCD- TSADL, MPADL-LC3, BERTL-HIALCC, MPADL-LC3 Method, m-SRC Model, Faster RCNN, RESNET-50, and DL algorithms accomplish lower CT values of 15.34sec, 12.81sec, 15.59sec, 16.76sec, 10.61sec, 19.06sec, 16.19sec, and 24.39sec, respectively.

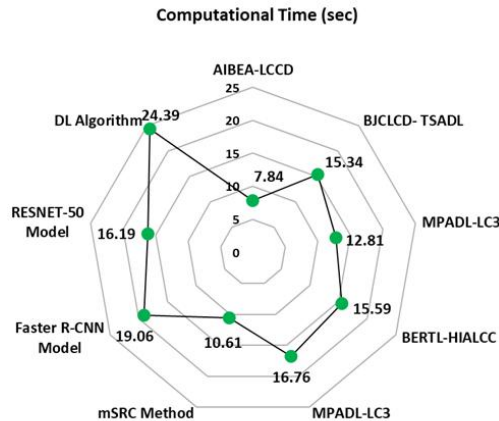


Fig. 13. CT analysis of AIBEA-LCCD methodology with existing classifiers.

V. CONCLUSION

In this manuscript, a novel AIBEA-LCCD approach has been presented for the precise and reliable diagnosis of LCC using HIs. At first, the AIBEA-LCCD algorithm applies image pre-processing utilizing the ABF to enrich the quality of images by noise reduction while upholding critical edges and details. Next, the CapsNet method has been applied for the extraction of features to capture spatial hierarchies and relationships among the features. At last, an ensemble of three approaches, namely DGRU, SNN, and DAE models are deployed for the LCC diagnosis process. To establish a good classification result of the AIBEA-LCCD approach, a huge sort of simulations were conducted on the benchmark image dataset. The widespread comparative outcomes certified the improvement of the AIBEA-LCCD approach compared to recent models.

Data Availability Statement: The data that support the findings of this study are openly available in Kaggle repository at <https://www.kaggle.com/datasets/andrewmvd/lung-and-colon-cancer-histopathological-images>, reference number [24].

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