

Advanced Severity Detection in Histopathological Ovarian Cancer: Rank-Based Leaf Wind Optimization and Alpha Piecewise Linear Fuzzy Techniques

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Abstract

Background: Ovarian cancer (OC) often goes undetected until advanced stages due to mild early symptoms.

Methods: This research proposes a novel methodology for assessing OC severity through histopathological image analysis, utilizing Rank-Based Leaf in Wind Optimization and Alpha Piecewise Linear Fuzzy techniques. It enhances tissue image quality through normalization and Contrast Limited Adaptive Histogram Equalization, employs ResNet 50 with Inception v4 for feature extraction, and uses a ranking layer to prioritize key features.

Results: The model achieved 99.25% accuracy and 97.98% precision, effectively classifying tumor severity levels under diagnostic uncertainty.

Conclusion: This robust approach enhances diagnostic accuracy, supports early detection, and improves treatment planning. Future work will explore cross-validation, model pruning, and real-time integration for clinical applications.

Keywords: Contrast Limited Adaptive Histogram Equalization, deep learning, histopathological images, normalization, ovarian cancer, severity prediction

Introduction

Ovarian cancer (OC) is the most prevalent malignancy in the female reproductive system, with the highest mortality rate among pelvic cancers.¹ Around 70% of cases are diagnosed at advanced stages (III and IV), characterized by distant metastases.² Targeted therapies include small-molecule inhibitors, antibody–drug conjugates, and monoclonal antibodies.³ Despite advancements, lymph node metastasis significantly elevates mortality and recurrence risks.⁴

The high death rates and difficulty in early diagnosis of OC necessitate effective severity detection in histopathology. Addressing these challenges requires innovative strategies for improved detection and classification. This is the first study to integrate Rank-Based Leaf Wind Optimization with ResNet-50, Inception V4, and an Alpha Piecewise Linear Fuzzy classifier for OC severity detection using histopathological images.

Major contributions of the proposed methodology are as follows:

- The research objective is to enhance the detection and classification of OC severity through advanced histopathological image analysis techniques.
- The ResNet 50 with Inception v4 (ResInV4) feature learner efficiently captures complex patterns in medical images. During feature extraction, dropout is applied to prevent overfitting by promoting generalization. This enhances robustness for tasks like OC diagnosis.
- The ranking convolutional neural network (CNN) eliminates the need for explicit segmentation by reordering feature maps based on their significance. It supports both supervised and unsupervised learning, enabling accurate classification by leveraging pairwise feature correlations and effective gradient flow during backpropagation.

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- The Alpha Piecewise Linear Fuzzy (APLF) technique improves classification accuracy by managing data uncertainty with fuzzy logic.

This is how the rest of the document is organized: The literature review is discussed in the “Literature Review” section. The “Proposed Methodology” section describes the suggested system, while the “Results and Discussions” section discusses the experimental results and discussion. In the “Conclusions” section, the article comes to an end.

Literature Review

Recent major research on severity detection in histopathological OC using Deep Learning (DL) is summarized as follows:

In a study by Farahani et al.,⁵ deep CNNs help pathologists identify OC histotypes, improving interobserver agreement. The study trained four AI models on a large dataset for classification.

In a study by Fahim et al.,⁶ Ovarian Net, a DL framework, diagnoses OC subtypes using histopathological images, incorporating squeeze-and-excitation and custom spatial attention for rich feature extraction.

In a study by Hatamikia et al.,⁷ AI is used to integrate genomic, transcriptomic, and imaging data, which increase high-grade serous OC understanding and improve diagnosis.

In a study by Wang et al.,⁸ DL helps diagnose OC with the ocular biopsy method, accurately describing second

harmonic generation images of freshly removed unstained ovarian tumors.

Problem statement

Existing methods like CNN⁶ and artificial neural network (ANN)⁸ struggle with overfitting and image quality variability, leading to inconsistent diagnoses. Deep conventional neural network (DCNN)⁵ and multilayer perceptron networks (MPN)⁷ face challenges in integrating diverse datasets, limiting predictive accuracy for OC outcomes. The proposed Rank-Based Leaf in Wind Optimization and Alpha Piecewise Linear Fuzzy (RBLAPF) significantly improves prediction accuracy for endometriosis by effectively analyzing and integrating clinical and imaging data. This enhances prediction reliability, paving the way for better automated systems and personalized treatment in OC care.

Proposed Methodology

The input images are sourced from the OC dataset,⁹ OC Subtype Classification dataset,¹⁰ UBC-OCEAN dataset,¹¹ and OC TMA-Stanford Database¹² followed by preprocessing techniques like normalization, regions of interest (ROI) extraction, and Contrast Limited Adaptive Histogram Equalization (CLAHE). The preprocessed image is augmented using scaling, jittering, intensity shifting, and flipping, and the augmented images are then fed into the Rank-Based Leaf wind resnet Inceptional V4 CNN (RBLICNN) model, which combines ResInV4 and a Ranking Layer CNN for feature

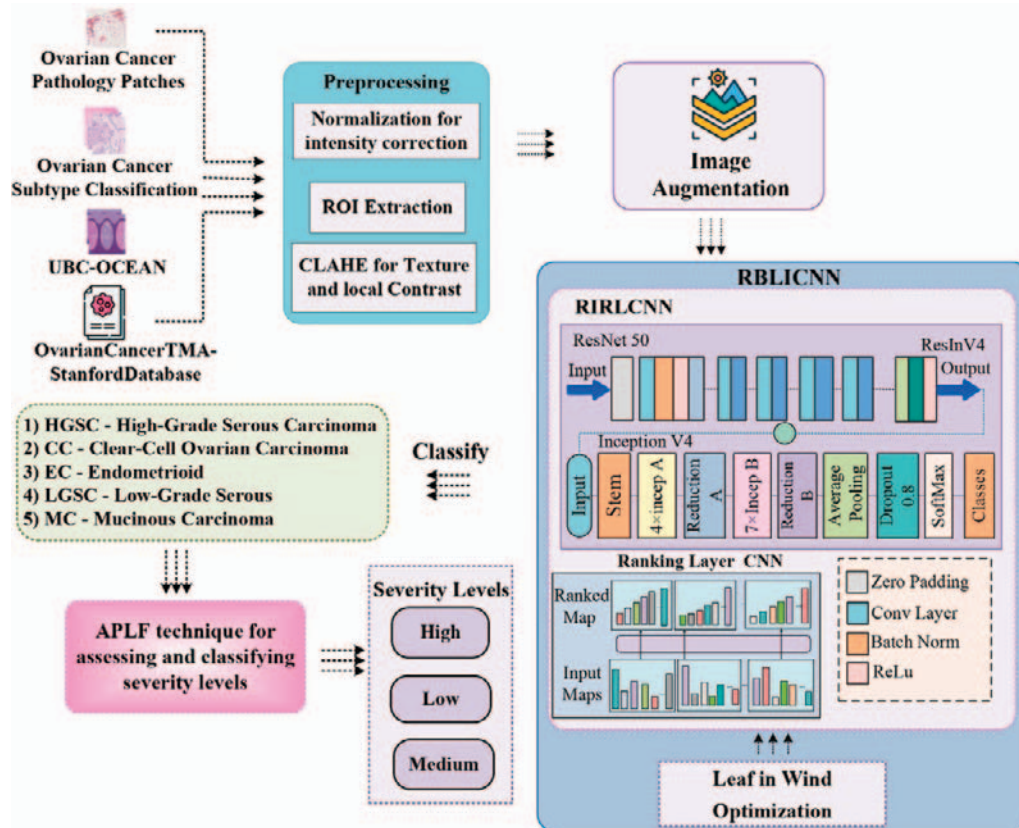


FIG. 1. Overview of the proposed RBLAPF framework. RBLAPF, Rank-Based Leaf in Wind Optimization and Alpha Piecewise Linear Fuzzy.

extraction. The Leaf in Wind Optimization (LWO) method is used for parameter optimization, while the APLF technique, utilizing fuzzy logic, classifies OC severity into high, low, or medium levels. Figure 1 illustrates the proposed methodology.

Preprocessing

Preprocessing¹³ for histopathological diagnosis of OC involves a series of image enhancement techniques to standardize and improve the quality of stained tissue images. Given the inherent variability in staining processes and digital scanning, methods such as log-normalization and CLAHE¹⁴ are employed. The normalization¹⁵ D_{norm} matrix is employed in the generation of color normalization. In Red Green Blue images J_{norm} can be shown in Equation (1).

$$J_{norm} = J_p f^{-X_U D_{norm}} \quad (1)$$

where, X_U represents the target stain appearance matrix, f represents the target stain, and D_{norm} represents the size transformation matrix in relation to the number of color channels with stain concentration and J_p incident light intensity. ROI are automatically detected based on nuclear density to assess cell proliferation in OC histology. The preprocessed image output is analyzed through augmentation.

Data augmentation

The preprocessed image is subjected to data augmentation. It contains techniques like scaling, flipping, intensity shifting, and rotation.¹⁶ These augmentations introduce variability in size, orientation, lighting, and perspective, enhancing the model's generalization ability.

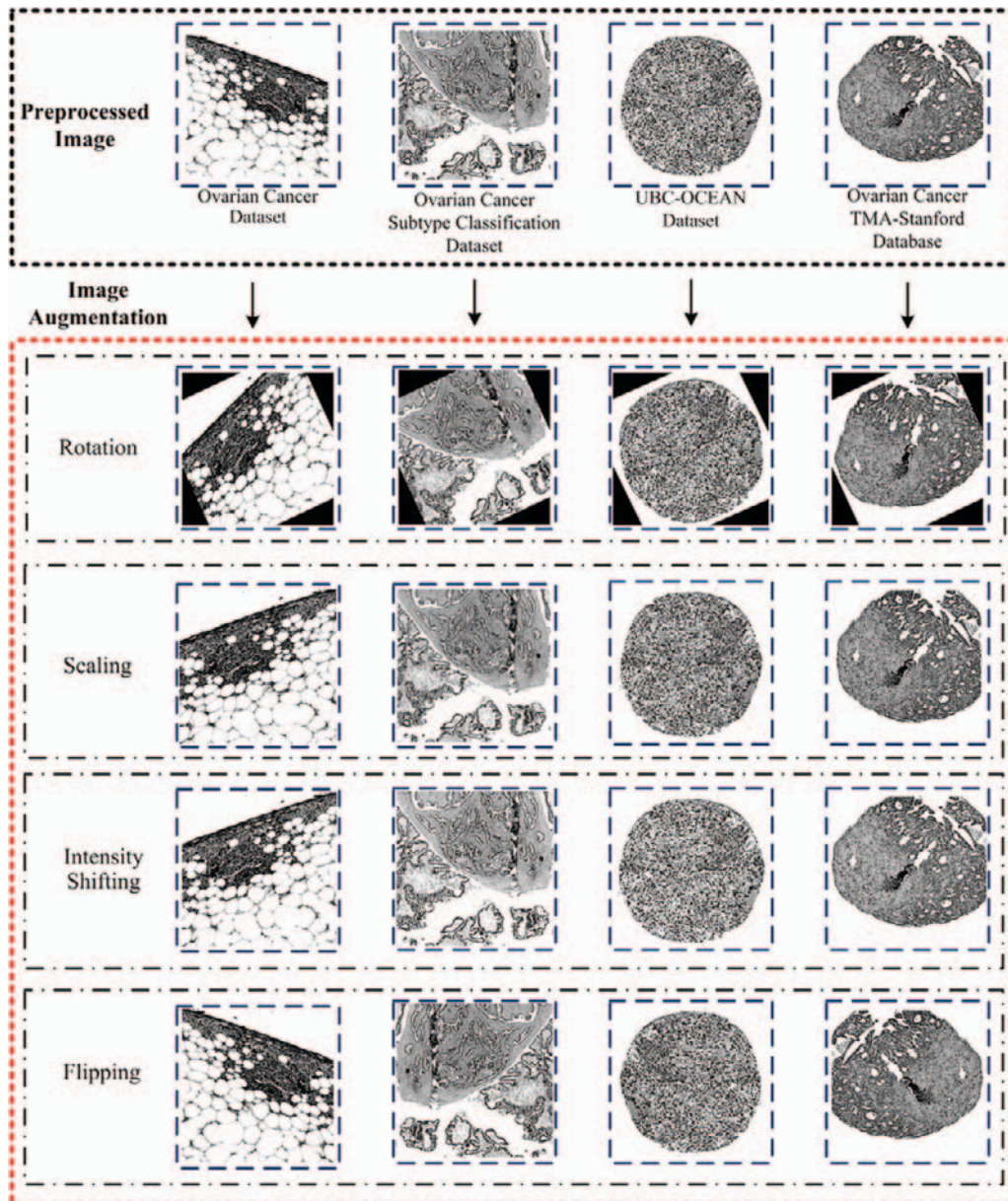


FIG. 2. Image augmentation.

Rotation. It is an augmentation technique used to rotate an image by a specific angle. It can assist in producing variations in the orientation of the image's objects. The image is rotated at a random angle between -90° and $+90^\circ$.

Scaling. This technique involves resizing the image by increasing or decreasing its dimensions.

It helps simulate objects at different distances or zoom levels. A random scaling factor is applied to expand or shrink the image while preserving the aspect ratio.

Intensity shifting. This entails altering each pixel's intensity in the image by adding or subtracting a fixed value. It helps simulate lighting variations and camera exposure changes. A random shift value is applied across the entire image to adjust brightness levels uniformly.

Flipping. It is an augmentation technique where the image is flipped horizontally or vertically. It helps simulate different viewing angles and mirror-like perspectives. This enhances model robustness by exposing it to diverse orientations. Figure 2 illustrates the applied image augmentation methods.

Rank-Based Leaf wind resnet Inceptional V4 CNN

RBLICNN integrates a ranking layer with a hybrid ResNet-50 and Inception V4 architecture to improve image classification, particularly for medical diagnostics like OC.¹⁷ It prioritizes feature selection by reordering feature map elements to emphasize key attributes and minimize noise. LWO enhances image clarity, improving the visibility of cellular structures crucial for diagnosis. The preprocessed image is then fed into the ResInV4 section¹⁸ for superior feature extraction and classification.

Feature learner using ResInV4. The ResInV4 hybrid architecture combines ResNet-50 and Inception V4 to improve training efficiency and address the vanishing gradient problem by bypassing certain stages. It integrates multiple kernel sizes in a single layer, enhancing feature recognition for complex tasks like OC diagnosis. This method ensures high accuracy by effectively extracting significant features from medical images. Residual connections and varying filter sizes help mitigate overfitting and variability in image quality. In ResInV4, dropout is widely used to prevent overfitting in DL models. In order to force the network to learn more resilient and independent features, it randomly removes neurons and their connections throughout each training cycle. By doing this, dropout discourages coadaptation among neurons and reduces reliance on specific units. This randomness creates an ensemble effect, where the model learns from many different "thinned" versions of itself. At test time, the full network is used with scaled weights to average the learned behaviors. Overall, dropout enhances generalization and model stability.

Ranking layer in CNN. CNN uses a ranking layer¹⁹ that prioritizes feature map ordering over absolute values. Let G the input feature map be with O elements, where each element G_j corresponds to the j th feature in the map. The ranked version of this feature map is denoted as S_j where each element S_j represents j th smallest element G . Index of

j th smallest element on G is denoted as $\pi(j)$, leading to the relationship shown in Equation (2).

$S_j = G_{\pi(j)}. \quad (2)$

Data segmentation is not necessary for our research because the ranking CNN²⁰ can accurately classify both supervised and unsupervised data on its own. The ranking layer rearranges the feature map's elements according to their values as it propagates forward. Pairwise correlations between the input feature map G and the backward propagation and its ranked version S . It is possible to return the gradients from the loss function to their respective elements G .

The Loss function of $M(\cdot)$ on each instance can be in Equation (3),

$$M(z_j, g(y_j, x)) = \sum_{j=1}^R Q_{zj} \left(\prod \right) \log Q_{g(y_j, x)} \left(\prod \right) \quad (3)$$

where, Q_{zj} represents the probability distribution in relation to reality, $Q_{g(y_j, x)}$ represents the distribution of probability with respect to the predicted rank list $\prod$. For optimizing parameters undergoes LWO.

Leaf in Wind Optimization. LWO²¹ is used to improve the visibility of sick features and cellular structures, which is crucial for an accurate diagnosis.

Fitness function.

$$\text{fitness function} = \text{Min} (M(z_j, g(y_j, x))) \quad (4)$$

TABLE 1. PROPOSED METHODOLOGY PSEUDOCODE

```

Initialize parameters:
dataset = load_images("path/to/dataset")
preprocessed_images = preprocess_images(dataset)
Step 1: Feature Learner
  selected_features = feature_selection(preprocessed_images)
  train_set, test_set = split_dataset(selected_features)
  model = CreateResInV4()
Step 2: Ranking Layer
  cnn_model = train_cnn(train_set)
  ranked_features = rank_features(cnn_model, test_set)
Step 3: Optimization using LWO
  Initialize leaves:
    leaves = InitializeLeaves(num_leaves, leaf_dimensions)
  For each leaf in leaves:
    fitness = ComputeFitness(leaf, image_features)
  For each leaf in leaves:
    Update LeafPosition(leaf, fitness)
  For each leaf in leaves:
    UpdateLeafPositionWithWind(leaf)
  optimized_parameters = OptimizeParameters(leaves)
Step 4: Alpha Piecewise Linear Fuzzy technique
  severity_levels = [High, Low, Medium]
  FOR image IN test_set
    fuzzy_number = extract_fuzzy_number(image)
    severity = assess_severity(fuzzy_number)
    severity_levels.APPEND(severity)
END FUNCTION

```

Equation (4) represents minimizing the loss function. Performance analyses like standard deviation, mean square error, entropy, and correlation coefficient are used to evaluate the effectiveness of image enhancement through a fitness function. Optimized parameters are then passed from LWO to APLF by calibrating triangular fuzzy numbers and adjusting fuzziness levels for improved membership sensitivity. This approach ensures precise classification of severity levels in histopathological analysis.

APLF technique for assessing and classifying severity levels. When diagnosing OC by histopathological image analysis, the APLF technique²² provides a strong foundation for identifying severity levels, such as low, middle, and high. Triangular fuzzy numbers are essential because of their membership functions. Table 1 shows the proposed methodology pseudocode.

Results and Discussion

The effectiveness of this proposed approach has been implemented on the Python platform. It has been against existing methods, which include the DCNN,⁵ CNN,⁶ MPN,⁷ and ANN²³ to assess its performance.

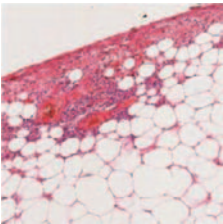
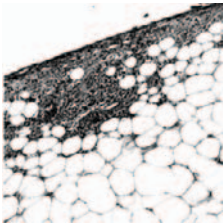
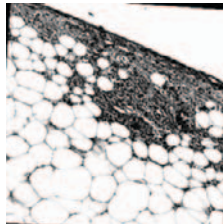
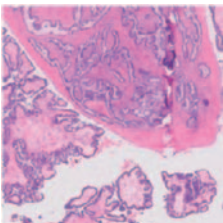
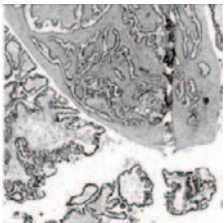
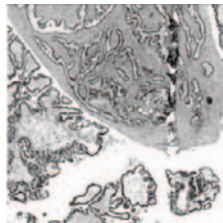
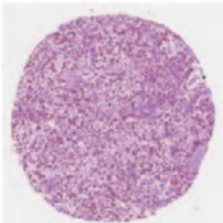
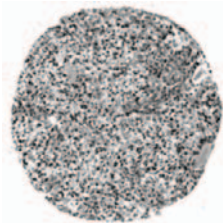
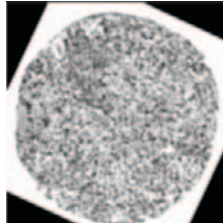
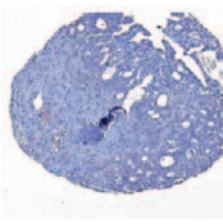
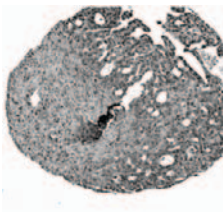
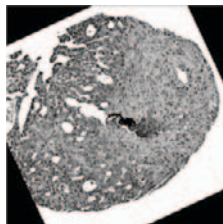
Pretraining

The training configuration includes 100 epochs with 100 iterations per epoch, 0.001 learning rate, and the dataset comprises OC images from reliable medical databases. The implementation is carried out using Google Colab on a Google Compute Engine backend, equipped with RAM 12.67 GB and disk space with 107.72 GB.

Dataset descriptions

The OC Pathology Patches dataset consists of 4032 labeled histological image patches of ovarian tissue, each with a resolution of 256×256 pixels in PNG format. This dataset is useful for machine learning-based classification of cancerous versus noncancerous regions. The OC Classification dataset includes 2,748 images; each sized at 224×224 pixels and saved in PNG format. It contains extracted features and is categorized into benign and malignant cases, supporting early diagnosis through classification algorithms. The UBC-OCEAN dataset provides 7080 images of variable sizes in PNG format, along with genomic and clinical data such as gene expression, DNA methylation, and protein levels, which are valuable for OC subtype classification. Lastly, the OC TMA-Stanford Database offers 20 high-resolution

TABLE 2. OUTCOME OF THE DATASETS

Dataset	Input images	Preprocessed images	Augmented	Classification image	Severity prediction
Dataset 1				High-grade serous carcinoma	High
Dataset 2				Low-grade serous	Low
Dataset 3				Clear cell ovarian carcinoma	Medium
Dataset 4				Mucinous carcinoma	Low

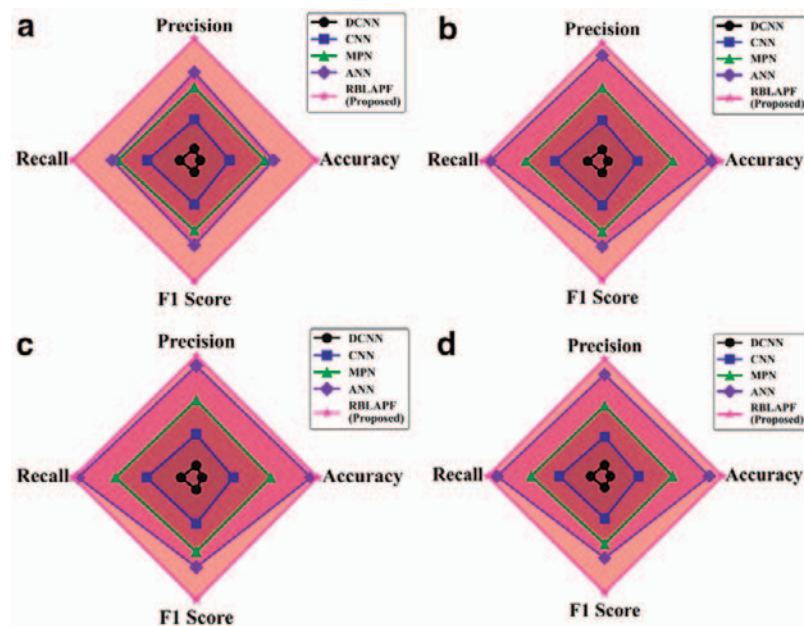


FIG. 3. Comparative analysis of performance metrics: (a) OC Pathology Patches dataset, (b) OC Classification dataset, (c) Outlier Detection (UBC-OCEAN) dataset, and (d) OC TMA-Stanford Database. OC, ovarian cancer.

tissue microarray (TMA) images in JPG format, each with a size of 1504×1440 pixels. These images are labeled with various subtypes such as clear cell, endometrioid, and mucinous, making them useful for training and evaluating classification models.

Experimental results

The experimental results demonstrate a significant improvement when comparing the proposed methodology with existing practices. Metrics showing notable gains, including precision, accuracy, F1-score, and recall, among others, show the effectiveness of the proposed method. The outcomes of the datasets are given in Table 2.

Comparative analysis of proposed method and existing techniques for OC severity prediction. Figure 3 presents a comparative performance analysis between existing models

and the proposed RBLAPF method across four OC-related datasets. In Figure 3(a), the OC Pathology Patches dataset shows that the existing models DCNN, CNN, MPN, and ANN achieved accuracy of 52%, 60%, 72%, and 80%, whereas the proposed model outperformed them with 99.25% accuracy, 97.98% precision, 97.89% recall, and a 98.23 F1-score. Figure 3(b) shows that on the OC Classification dataset, the proposed method achieved 99.02% accuracy, 98.32% precision, 97.34% recall, and a 97.38 F1-score, surpassing all baselines. In Figure 3(c), on the UBC-OCEAN dataset, the proposed model reached 98.92% accuracy, 97.32% precision, 98.24% recall, and a 98.18 F1-score. In Figure 3(d), the OC TMA-Stanford Database achieved 98.22% accuracy, 96.32% precision, 98.74% recall, and a 98.58 F1-score. Across all datasets, the proposed RBLAPF consistently demonstrated superior performance over existing methods.

The comparative analysis of severity prediction techniques can be shown in Figure 4. Existing methods, such as

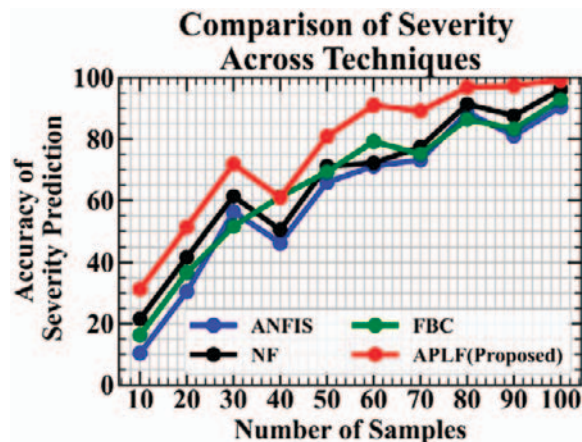


FIG. 4. Comparative analysis for severity prediction techniques.

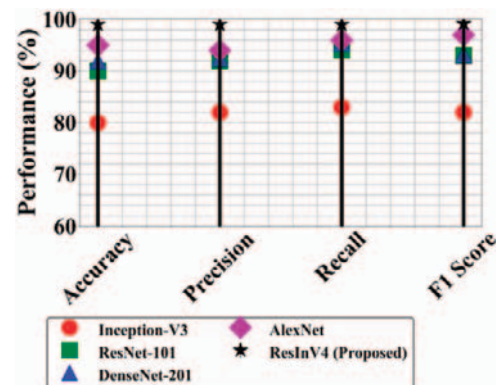


FIG. 5. Comparison of the proposed model with major DL models. DL, deep learning.

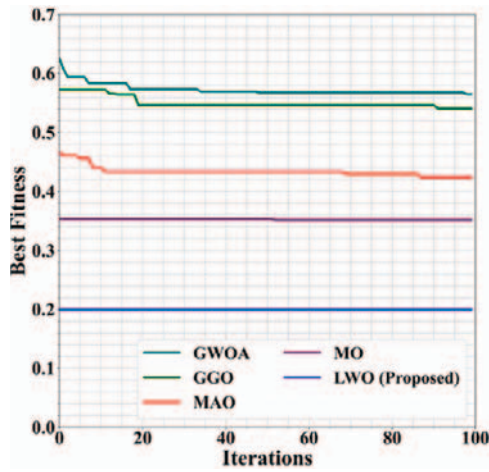


FIG. 6. Fitness analysis of optimization models.

the Adaptive Neural Fuzzy Inference System,²⁴ Neuro Fuzzy,²⁵ and Fuzzy Backstopping Control,²⁶ demonstrate lower accuracy in severity prediction when compared to the proposed method. The APLF (Alpha Piecewise Linear Fuzzy) achieved a highest accuracy of 98.96% in severity prediction over existing methods.

Figure 5 highlights the superior performance of the ResIn V4 model compared to major DL models like Inception-V3, ResNet-101, DenseNet-201, and AlexNet. ResIn V4 achieves 98% accuracy and nearly 99% in other metrics, significantly surpassing DenseNet-201 with 88% accuracy and others with lower results. This demonstrates ResIn V4's exceptional effectiveness in precision, recall, accuracy, and F1 score.

Fitness analysis. Figure 6 shows the fitness comparison of existing optimization models like Metaheuristic Optimization (MO),²⁷ Multiobjective Arithmetic Optimization (MAO),²⁸ Grey Wolf Optimization Algorithms (GWOA),²⁹ Greylag

Goose Optimization (GGO),³⁰ and the proposed LWO model over 100 iterations. The existing models like GWOA, GGO, MAO, and MO achieved fitness values of 0.62, 0.58, 0.48, and 0.36, while the proposed LWO attained the lowest fitness value of 0.20. The proposed LWO model has the lowest fitness value, which indicates that LWO achieves the highest accuracy in OC classification.

The training and validation accuracy-loss analysis for four datasets over 20 epochs can be shown in Figure 7. With matching training and validation losses of 0.3 and 0.2, the OC Pathology Patches dataset achieves 1.0 training accuracy and 0.90 validation accuracy in Figure 7(a). Figure 7(b) shows the OC Classification dataset with a training accuracy of 1.0 and a validation accuracy of 0.93; the training loss is 0.2, and the validation loss is 0.18. In Figure 7(c), the Outlier Detection (UBC-OCEAN) dataset records a training accuracy of 0.98 and validation accuracy of 0.91, with training and validation losses of 0.18 and 0.15. Figure 7(d) presents the OC TMA-Stanford Database, where the training accuracy reaches 0.98 and validation accuracy is 0.91, while the training and validation losses are 0.5 and 0.3.

The receiver operating characteristic (ROC) performance curve analysis for the proposed model applied to four distinct OC datasets can be shown in Figure 8. The OC Pathology Patches dataset (Dataset 1) achieved an area under the curve (AUC) of 0.994, the OC Classification datasets (Dataset 2) attained an AUC of 0.995, and the Outlier Detection (UBC-OCEAN) dataset (Dataset 3) showed an AUC of 0.996, while the OC TMA-Stanford Database (Dataset 4) has an AUC of 0.997. These results demonstrate the model's consistent and robust diagnostic capability across diverse datasets.

Discussion

The integration of AI in OC histopathological diagnosis, as proposed in the RBLICNN framework, necessitates

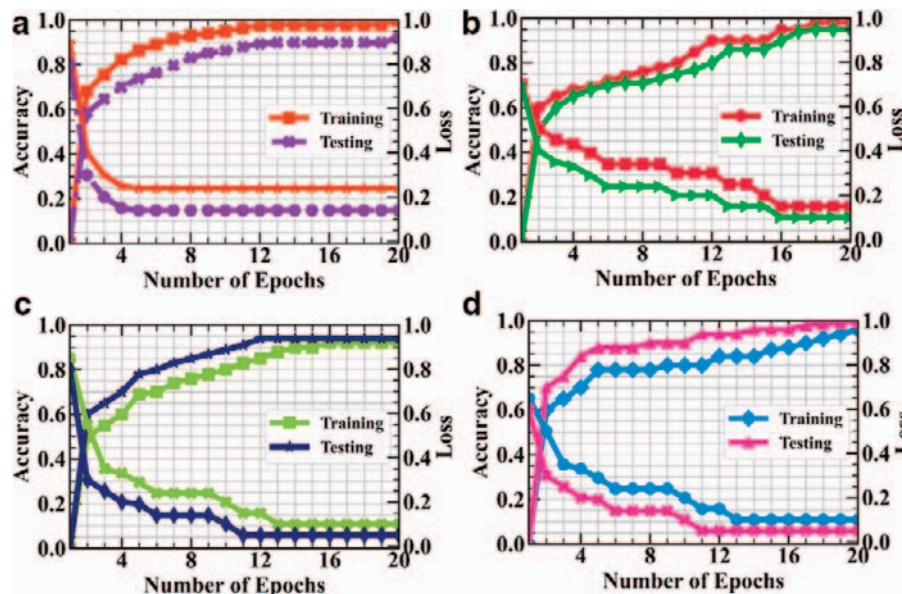


FIG. 7. Training and testing accuracy-loss analysis over 20 epochs. (a) OC Pathology Patches dataset, (b) OC Classification dataset, (c) Outlier Detection (UBC-OCEAN) dataset, and (d) OC TMA-Stanford Database.

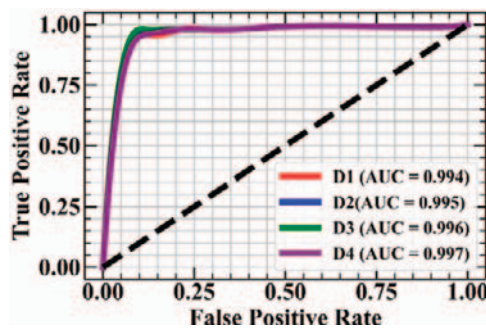


FIG. 8. ROC performance curve.

ethical considerations to ensure responsible use. Patient privacy is paramount, and all datasets are anonymized following standard protocols, aligning with health insurance portability and accountability act and general data protection regulation (GDPR) norms. The model design, including the ranking layer and LWO, supports fair predictions by emphasizing relevant features. Human oversight remains crucial, and AI should assist, not replace, clinical judgment. Ensuring transparency about AI involvement in diagnosis promotes patient trust and informed consent. Accountability mechanisms must be in place to address model misclassifications. Fairness audits and explainable AI methods can enhance interpretability and trustworthiness. Ethical deployment of AI tools requires continuous evaluation of their clinical impact. Overall, balancing innovation with ethical safeguards is key to responsible AI use in healthcare.

Conclusions

In conclusion, our research presents a histopathological analysis of OC, merging advanced image preprocessing with a robust classification framework. The RBLAPF significantly enhances diagnostic accuracy and tumor severity assessment, offering a reliable solution for early detection and effective treatment planning. The APLF technique adeptly classifies tumor severity levels while accommodating diagnostic uncertainty, demonstrating strong potential for clinical applications. The high accuracy and precision of our approach not only promise to improve diagnostic practices but also enhance patient outcomes in oncology. Although the proposed model demonstrates strong generalization across datasets, future work will explore additional techniques like cross-validation and model pruning to further reduce overfitting risks. In addition, aim to enhance the generalization capability of the RBLAPF framework by utilizing diverse datasets and integrating real-time processing capabilities to further advance clinical diagnostics in histopathology.

Authors' Contributions

All authors have made an equal contribution to the work. All authors reviewed the article.

Replication of Results

The authors warrant that the above work has not been previously published elsewhere, and no results were replicated.

Disclosure Statement

There are no existing financial conflicts.

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