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Multiscale Residual Attention Feature Fusion Network for Ovarian Cancer Subtype Classification

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Abstract
The classification of ovarian cancer into specific subtypes is essential for distinguishing tumor categories based on cellular morphology and tissue architecture observed in histopathological images. However, subtype classification remains challenging due to morphological similarities, variations in tissue patterns and limited discriminative feature representations. To solve these challenges, this research proposes a Multiscale Residual Attention Feature Fusion Network (MRAFF-Net) is introduced for automatic ovarian cancer subtype classification. The algorithm integrates multiscale feature extraction, residual learning, channel–spatial attention and adaptive feature fusion. First, histopathological images are resized and normalized, followed by parallel feature extraction at fine, intermediate and coarse scales. Residual connections preserve informative representations, while channel and spatial attention mechanisms emphasize discriminative tissue features. Subsequently, adaptive feature fusion combines complementary multiscale representations into a unified feature vector, which is passed to fully connected layers and a Softmax classifier to predict the ovarian cancer subtype. Performance is evaluated using accuracy, precision, recall, F1-score, specificity and the area under the Receiver Operating Characteristic Curve (ROC-AUC). The experimented results indicate an accuracy of 96.82% under the evaluated experimental conditions. Overall, MRAFF-Net integrates multiscale histopathological feature extraction and feature fusion for ovarian cancer subtype classification. Further evaluation using larger, independent, multicenter cohorts is required to assess generalizability and clinical applicability.

Keywords: Cancer Subtypes, Cellular Morphology, Feature Fusion, Histopathological Images, Ovarian Cancer, Tissue Architecture.

1. Introduction

Ovarian cancer is a heterogeneous type of cancer where there are several elements associated with tissue morphology, cell organization and progression of the disease in subtypes. The automatic discrimination between subtypes through histopathology images has become very important when it comes to diagnoses and treatment. Automatic diagnosis is challenging because of shared morphological structures, variations in staining and differences in tissue organization.Despite significant advances in Deep Learning (DL), accurate subtype classification remains challenging when discriminative features occur at different spatial scales.Existing researches have investigated the automatic diagnosis of ovarian masses through Computed Tomography(CT) andMagnetic Resonance Imaging(MRI) images [1], automatic detection of metastatic lesions of ovarian cancer in lymph nodes and omental tissues through multiple instance learning [2] and explainable and confidence-aware DL based automatic classification of ovarian tumors through ultrasound images [3].Several other research methodologies have explored CT sequence selection for the classification of ovarian tumors [4], histopathology foundation models for the classification of subtypes of ovarian cancer [5] and hierarchical multi-attention feature fusion for cross-scale medical image classification [6]. Although previous approaches address ovarian cancer diagnosis using different medical imaging modalities, variations in imaging techniques, extracted features and classification objectives highlight the need for histopathology-based subtype classification using multiscale morphological representations.

Further advances include ensemble DL networks for ovarian tumor segmentation and classification in computed tomography (CT) images [7] and attention embedding for ovarian cancer subtype classification and outlier detection [8] and explainable DL for ovarian cancer multiclass diagnosis [9]. Moreover, the segmentation-based approach was explored for enhancing SegFormer networks in ovarian tumor images [10] and Fuzzy DL was explored for detection and classification of ovarian cancer [11]. In addition, prior to surgery, successful

prediction of molecular subtyping of ovarian cancer has been achieved with multiparametric MRI feature fusion [12]. Despite these advances, the critical task of incorporating the multiscale histopathological characteristics, residual representation learning, channel-wise and spatial feature refinement and adaptive scale fusion are still key design goals for achieving accurate classification of subtypes. To address this problem, the proposed Multiscale Residual Attention Feature Fusion Network (MRAFF-Net) uses three-scale feature extraction, residual learning, channel attention, spatial attention and adaptive feature fusion. The network learns complementary morphological representations, identifies discriminative regional tissue characteristics and predicts the fusion weights for each scale before being fully connected for classification and Softmax probability estimation. The classification performance is evaluated using accuracy, precision, recall, F1-score, specificity and the area under the receiver operating characteristic curve (ROC-AUC) and the contributions of individual network components are evaluated by conducting ablation analyses.

The key points and rationale behind the proposed MRAFF-Net are the following:

- Existing solutions for classification of ovarian cancer provide insufficient multiscale feature representations and face difficulties with visual discrimination of similar classes within the histopathological images.
- MRAFF-Net integrates multiple scale feature extraction, residual learning and channel-spatial attention to enhance morphological feature representation.
- The adaptive feature fusion technique aids in classification of ovarian cancer subtypes through combining complementary feature representations on multiple scales. The effectiveness of the solution was assessed in terms of six metrics and ablation study.

Organization: Section 2 reviews existing methods and identifies the research gap. Section 3 explains the proposed MRAFF-Net algorithm, architecture, equations and pseudocode. Section 4 presents experimental results, Section 5 discusses the findings and limitations and Section 6 concludes the research and presents future research directions.

2. Background Study

Chaudhary, N. andDhunny, A. Z. (2025) [13] developed an Artificial Intelligence (AI) algorithm to detect early stage of breast cancer using histopathological biopsy images. However, additional validation is needed for the application of the method to classify ovarian cancer subtypes.

Chen, H., Song, Q. and Chen, G. (2025) [14] designed a light weight multi-frequency feature fusion with efficient attention network to detect breast cancer based on pathology images. The method's ability to discriminate ovarian cancer subtypes using histopathological images remains uncertain.

Chun, J., et al. (2026) [15] have presented an application of deep learning to the classification of ovarian cancer through whole-slide histopathology images. The model shows the possibility of the histological subtype classification, while additional validation through different patient samples should be performed.

Giourga, M., et al. (2024) [16] have explored the use of convolutional neural networks to classify ovarian masses on ultrasound images. But ultrasound-based ovarian mass classification differs from histopathology-based one by the features used for subtype identification.

Hong, T., et al. (2026) [17] have proposed a dual center multimodal DL approach to prediction of types I and II of ovarian cancer. More research is needed to assess the performance for detailed histological subtypes.

Khalil, I., et al. (2024) [18] proposedOptical Coherence Tomography Network(OCTNet) algorithm based on InceptionV3 and multi-scale attention feature fusion for retinal OCT image classification. It solves the multi-scale features problem, but it cannot be applied to the ovarian histopathology data.

Liu, P., et al. (2025) [19] proposed Ovarian Tumor Classification Network (OTC-NET) for multimodal diagnosis of ovarian cancer in Ovarian-Adnexal Reporting and Data System (O-RADS) category 4 masses. Diagnosis of the mass by using imaging and its histopathology subtype classification are two different tasks.

Nannepaga, J. S., et al. (2026) [20] used the DL for the diagnosis of for 7,12-Dimethylbenz[a]anthracene (DMBA)-Induced Ovarian Cancer Detection histopathologybased on Cancer Antigen 125 (CA-125) biomarker. Validation in terms of the human histopathology data is required to check the applicability of the algorithm.

Nasir, I. M., et al. (2024) [21] designed a multi-feature attention network for the classification of breast cancer. The multi-feature representation approach provides a relevant methodological reference point, but validation on ovarian histopathology images is required.

Pulido, D. and Arias-Mendoza, N. (2026) [22] proposed a DL method to recognize histotypes of ovarian cancer based on whole-slide images. Analyzing the ability to generalize for each class in the independent dataset can give a better understanding of the strength of the proposed model.

Song, H. J., Cho, Y. S. and Kim, Y. S. (2026) [23] examined various approaches for feature extraction, aggregation and classification to identify subtypes of ovarian cancer from whole-slide images. This work highlights the importance of feature representation and aggregation, motivating the investigation of residual multiscale feature fusion.

Tarek, Z. and Hassan, E. (2026) [24] introduced rehearsal-based continual learning to avoid catastrophic forgetting in ovarian cancer subtyping. It is necessary to test the approach under varying data distribution and sample selection.

Xiang, H., et al. (2024) [25] designed an interpretable multimodal model for ovarian cancer diagnosis. The contribution of individual modalities and generalization of the model across clinical environments need to be explored.

Xu, D., et al. (2025) [26] combined the hybrid Convolutional Neural Network (CNN)–transformer approach with a discriminator in order to classify an ovarian tumor according to its ultrasound images. The application of the developed method to the histopathological subtyping should be considered independently since are based on the different input and features extraction approaches.

Zhang, M., et al. (2026) [27] presented a DL approach for prognosis prediction of primary mucinous ovarian carcinoma using histopathological images. Prognosis prediction of carcinoma is a distinct task from ovarian cancer classification.

Table 1: Background Study of Existing Methods for Ovarian Cancer Classification

Authors & Year	**Concept**	**Methods Used**	**Identified Gap**	**Limitation or Further Need**
Zubair, M., et al. (2025) [28]	Gastric cancer classification	Multi-channel attention, transfer learning	Adaptation to ovarian histopathology	Cross-domain applicability requires validation
Garcia-Atutxa, I., et al. (2025) [29]	Ovarian tumor classification	Early fusion, hybrid CNN–Transformer	Histopathological subtype classification	Ultrasound and histopathology use different image characteristics
Fahim, T. A., et al. (2024) [30]	Ovarian cancer subtype classification	Ovarian Cancer Network (OVANet), dual-attention mechanism	Further evaluation of multi-scale feature fusion	Independent-dataset robustness needs assessment
Kalmani, V. H., et al. (2026) [31]	Ovarian cancer subtype classification	Attention-guided deep learning	Improved discrimination of similar subtypes	External validation needs assessment
Li, D., et al. (2024) [32]	Thoracic disease diagnosis	Multi-branch residual attention network	Application to ovarian histopathology	Original task concerns thoracic disease
Ahmed, A. and Zeng, X. (2025) [33]	Ovarian histology classification	Domain-generalized deep learning	Robust multi-scale subtype representation	Domain-shift robustness needs assessment
Saha, A. K., et al. (2025)	Ovarian histopathology	Enhanced deep learning model	Improved discrimination among	Performance across diverse datasets needs

[34]	classification		similar subtypes	assessment
Saleem, M. S., et al. (2026) [35]	Ovarian cancer subtype classification	Differential sparse attention, DenseNet121	Integration of complementary multi-scale features	Comparative and external validation is needed

Table 1 presents related approaches with respect to the type of classification problem, feature extraction method and other required aspects of the methodology. This comparison motivates the investigation of residual multiscale feature fusion for ovarian cancer subtype classification.

2.1. Research Gap

Existing ovarian cancer classification methods have been investigated by focusing on feature extraction using histopathological analysis, attention mechanism, multi-modality learning and whole-slide image classification. However, distinguishing cancer subtypes with similar morphological characteristics remains challenging because both cellular and tissue-level information must be captured. An important direction is to investigate whether combining residual connections, multiscale feature extraction and attention-guided fusion can address this challenge. MRAFF-Net addresses this objective by extracting multilevel histopathological features while preserving informative representations through residual connections. The effectiveness requires class-wise evaluation, ablation analysis and independent validation.

3. Proposed Methodology

This section describes the MRAFF-Net algorithm, overall architecture, workflow, multiscale residual feature extraction, channel–spatial attention and adaptive feature fusion mechanisms. The mathematical equations and pseudocode describe the computational process, from histopathological image acquisition and feature refinement to ovarian cancer subtype classification and probability prediction.

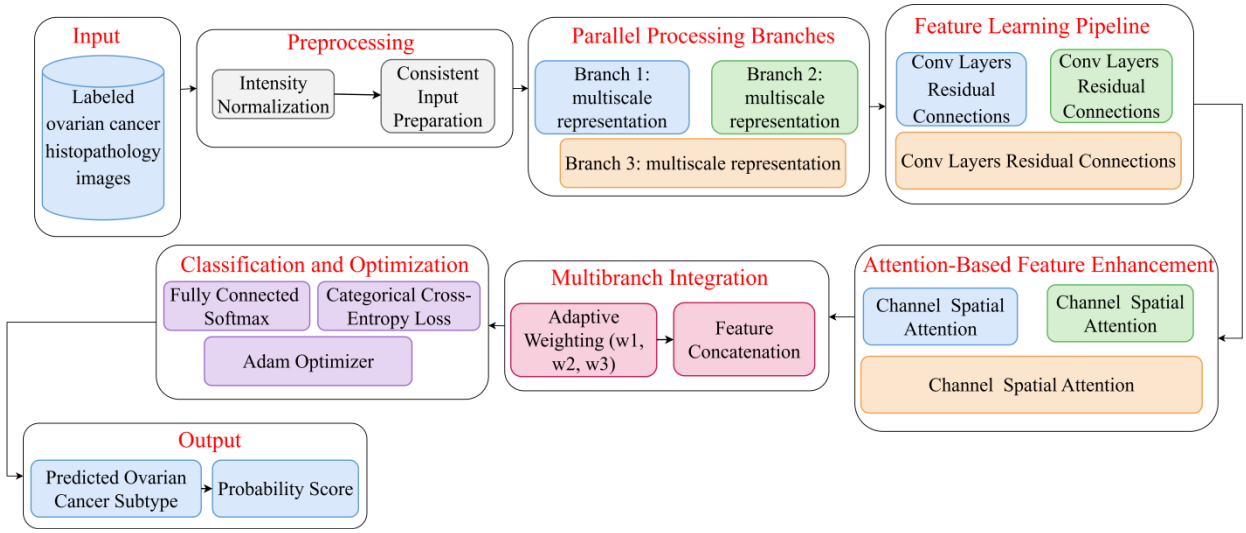


Figure 1: Structural Design of the MRAFF-Net Classification System

Figure 1 above illustrates the whole process flow from the input of images through preprocessing, parallel multi-scale processing, feature enhancement and finally subtype classification. The output is the subtype of ovarian cancer together with the score associated with each test image.

3.1. Dataset Description

The dataset description includes TCGA-OV genomic and clinical data (approximately 500 samples), Gene Expression Omnibus (GEO) microarray data (approximately 185 datasets, including GSE26712) and a local clinical dataset comprising approximately 200 patients with ultrasound/MRI images, Cancer Antigen 125 (CA-125)biomarker value, age, stage of cancer and medical history. The data comprise molecular, clinical and imaging characteristics intended to support ovarian cancer subtype classification. The data are preprocessed by handling missing values and applying augmentation to the training set to address class imbalance. The dataset is then divided into training, validation and test subsets. The classification targets are serous, endometrioid,

mucinous, clear cell and benign classes, subject to confirmation that the corresponding labels are available and consistently mapped across the datasets.

3.2 Proposed Algorithm: MRAFF-Net

The proposed Multiscale Residual Attention Feature Fusion Network (MRAFF-Net) utilizes parallel convolutional networks to obtain fine-grained micro feature information of the cells, intermediate tissue feature information and overall morphologic feature information by processing the histopathological images of ovarian cancer. The network integrates four components: multiscale convolutional feature extraction at different spatial resolutions, residual learning to preserve informative features and support gradient propagation, attention-based feature refinement to emphasize diagnostically relevant regions and adaptive feature fusion to combine complementary representations for subtype discrimination. Optimized convolutional operations, batch processing, transfer learning andGraphics Processing Unit (GPU)acceleration can enhance the scalability of MRAFF-Net. The integrated components are designed to address the limitations of single-scale feature extraction, information loss, irrelevant feature responses and difficulties in distinguishing visually similar ovarian cancer subtypes. In clinical workflows, MRAFF-Net could support pathologists in assessing ovarian cancer subtypes from histopathological images. Its generalizability should first be evaluated using independent, multicenter clinical data and its computational efficiency and classification performance should be compared with established deep learning models.

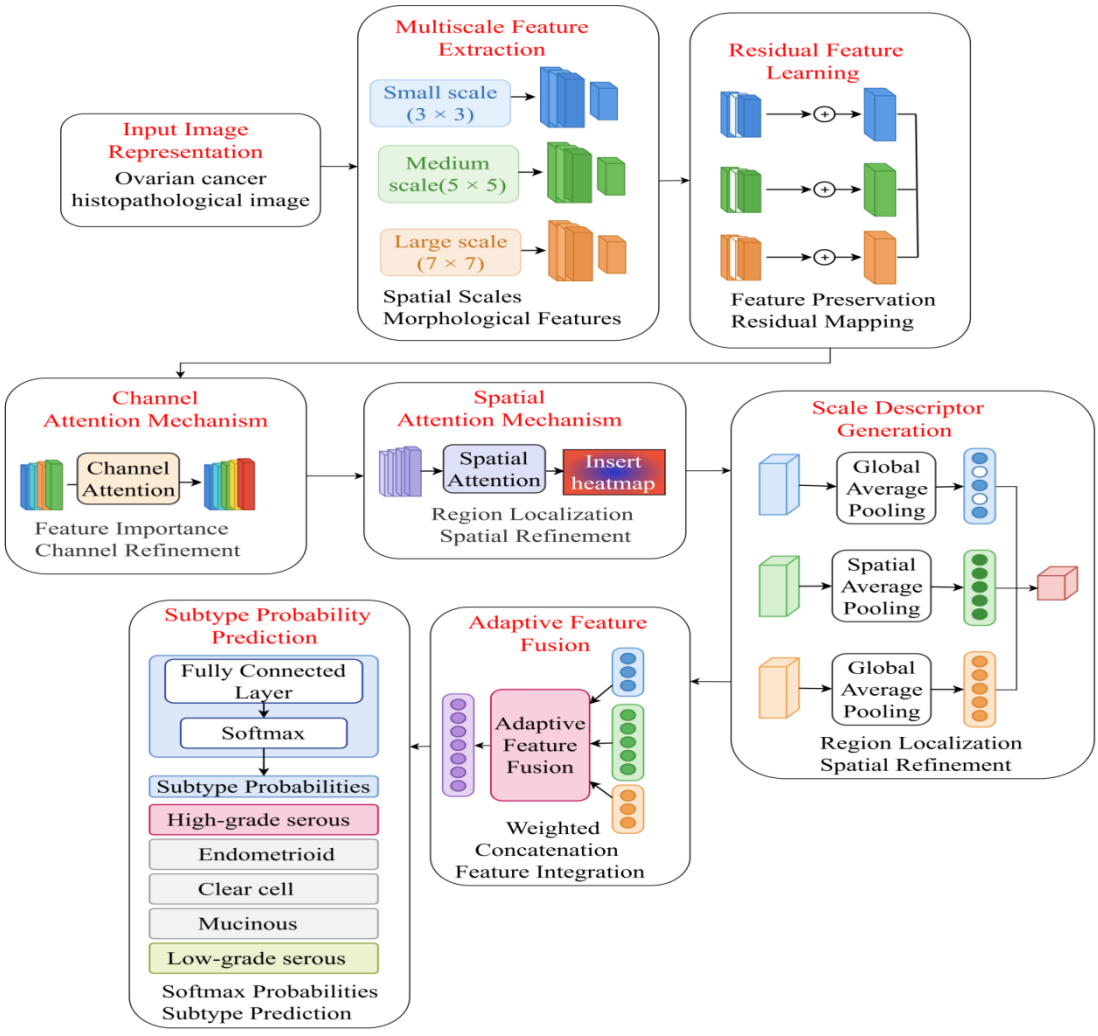


Figure 2: Algorithmic Workflow of MRAFF-Net

Figure 2 illustrates multiscale feature extraction, residual learning, channel–spatial attention refinement and adaptive feature fusion to learn discriminative ovarian cancer morphological features. The fused representation undergoes Softmax classification to predict the ovarian cancer subtype and corresponding class probabilities.

$$X \in \mathbb{R}^{H \times W \times C} \qquad (1)$$

Equation (1) represents X as the input histopathological image, H and W as image height and width and$C$ as the number of channels. This equation is the representation with inputs that is fed to the MRAFF-Net in order to process the image.

$$X_n = \frac{X-\mu_X}{\sigma_X+\epsilon} \qquad (2)$$

Equation (2) represents X_n as the normalized image, μ_X as mean intensity, σ_X as standard deviation andϵ as a small constant. This equation is used to normalize the intensities in the image so that features can be extracted consistently.

$$X_s = \mathscr{R}_s(X_n), \quad s \in \{1,2,3\} \qquad (3)$$

Equation (3) represents X_s as the image at scale s and$\mathscr{R}_s$ as the resizing operation. This equation generates multiple image scales that give information on the detail of the cells, the pattern of the tissues and the overall morphology.

$$F_s = \phi(W_s * X_s + b_s) \qquad (4)$$

Equation (4) represents F_s as the extracted feature map, W_s as convolutional weights, b_s as bias andϕ as the activation function. This equation is used for extracting the complementary morphological features at different spatial scales.

3.3 Multiscale Residual Feature Extraction and Attention Refinement

The MRAFF-Net processes ovarian cancer histopathological images through parallel convolutional pathways to extract fine-grained cellular details, intermediate tissue patterns and global morphological characteristics at different spatial scales. Residual connections preserve important feature information and facilitate deep feature learning, while the attention mechanism emphasizes diagnostically relevant regions and suppresses less informative features to improve discrimination between visually similar ovarian cancer subtypes.

$$U_s = \phi\big(\mathrm{BN}(W_{s,1} * F_s + b_{s,1})\big) \qquad (5)$$

Equation (5) represents U_s as the intermediate feature map, $W_{s,1}$ as convolutional weights, $b_{s,1}$ as bias and BN as batch normalization. This equation refines the learned features and stabilizes the training process.

$$V_s = \mathrm{BN}(W_{s,2} * U_s + b_{s,2}) \qquad (6)$$

Equation (6)representsV_s as the second convolutional output, $W_{s,2}$ as convolutional weights, U_s as intermediate features and$b_{s,2}$ as bias. This equation is learned first morphological representation, followed by residual integration.

$$R_s = \phi(V_s + S_s(F_s)) \qquad (7)$$

Equation (7) represents R_s as the residual feature map, V_s as transformed features andS_s as the shortcut mapping. This equation is applied to integrate the original feature, transformed feature to keep information and improve gradient propagation.

$$G_s(c) = \frac{1}{H_s W_s}\sum_{i=1}^{H_s}\sum_{j=1}^{W_s} R_s(i,j,c) \qquad (8)$$

Equation (8) represents $G_s(c)$ as the pooled descriptor for channel c andH_s and W_s as feature-map dimensions. This equation is a summary of spatial information that is used to create channel descriptors for attention processing.

$$A_s^{ch} = \sigma\big(W_{s,2}^{ch}\delta(W_{s,1}^{ch}G_s)\big) \qquad (9)$$

Equation (9) represents A_s^{ch} as channel-attention weights, G_s as the pooled descriptor and$W_{s,1}^{ch}$ and $W_{s,2}^{ch}$ as learnable weight matrices. The equation is used to determine the informative feature channels and the importance weights that are used in better representation of features.

$$C_s = R_s \odot A_s^{ch} \qquad (10)$$

Equation (10) represents C_s as the channel-refined feature map, R_s as the residual feature map andA_s^{ch} as channel-attention weights. This equation emphasizes informative channels and suppresses less informative feature responses.

$$A_s^{sp} = \sigma\left(W_s^{sp} * [\mathrm{Avg}_c(C_s) \| \mathrm{Max}_c(C_s)]\right) \quad (11)$$

Equation (11) represents A_s^{sp} as the spatial-attention map, W_s^{sp} as convolutional weights andAvg_c and Max_c as channel-wise pooling operations. This equation represents areas of significance, in which the properties of the cells/tissues are discriminative.

$$Q_s = C_s \odot A_s^{sp} \quad (12)$$

Equation (12) represents Q_s as the spatially refined feature map, C_s as channel-refined features andA_s^{sp} as spatial-attention weights. This equation enhances the parts of the image, which are meaningful and diminishes parts of the image, which are not.

$$z_s = \mathrm{GAP}(Q_s) \quad (13)$$

Equation (13) represents z_s as the feature descriptor at scale s andQ_s as the attention-refined feature map. Each refined feature map is transformed into a small vector by this equation which is used for adaptive fusion.

3.4 Adaptive Feature Fusion and Ovarian Cancer Subtype Classification

The adaptive feature-fusion mechanism combines refined multiscale representations from different convolutional pathways into a unified discriminative feature representation that captures complementary morphological characteristics. The fused features are passed through classification layers to predict ovarian cancer subtypes and the model's performance is evaluated using accuracy, precision, sensitivity, specificity and F1-score.

$$\alpha_s = \frac{\exp(w_s^{\mathrm{T}} z_s)}{\sum_{k=1}^{3} \exp(w_k^{\mathrm{T}} z_k)} \quad (14)$$

Equation (14) represents α_s as the fusion weight, w_s as the learnable scoring vector andz_s as the corresponding scale descriptor. This equation is used for the calculation of the relative importance of each scale and in order to normalize the fusion weights.

$$F_{\mathrm{fused}} = \alpha_1 z_1 \| \alpha_2 z_2 \| \alpha_3 z_3 \quad (15)$$

Equation (15) represents F_{fused} as the fused feature vector, z_1, z_2, z_3 as multiscale descriptors and$\alpha_1, \alpha_2, \alpha_3$ as fusion weights. This equation incorporates multiscale features that are complementary and it defines the as a single feature to classify subtypes.

$$h = \phi(W_f F_{\mathrm{fused}} + b_f) \quad (16)$$

Equation (16) represents h as the projected feature vector, W_f as the learnable weight matrix, F_{fused} as the fused features andb_f as bias. This equation is used to convert fused features into a discriminative representation to be used in classification.

$$o = W_o h + b_o \quad (17)$$

Equation (17) represents o as the classification-logit vector, W_o as classification weights, h as projected features andb_o as classification biasThis equation yields a classification score for each of the different kinds of ovarian cancer.

$$p_j = \frac{\exp(o_j)}{\sum_{k=1}^{K} \exp(o_k)} (18)$$

Equation (18) represents p_j as the predicted probability for class j, o_j as its logit and$K$ as the number of target classes. The most likely subtype is determined by the scores obtained in the classification, which are normalized to probabilities in this equation.

$$\mathscr{L}_{CE} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{K} y_{ij}\log(p_{ij}+\epsilon) \qquad (19)$$

Equation (19) represents $\mathscr{L}_{CE}$ as classification loss, N as the number of samples, y_{ij} as the actual class label andp_{ij} as the predicted probability. It is used to measure the prediction error and to train the network.

$$\theta_{t+1} = \theta_t - \eta\frac{\hat{m}_t}{\sqrt{\hat{v}_t}+\epsilon} \quad (20)$$

Equation (20) represents θ_t as current model parameters, η as the learning rate and$\hat{m}_t$ and $\hat{v}_t$ as bias-corrected first- and second-moment estimates in Adam. In this equation, parameters are updated for network to minimize the classification losses and predict sub-type of ovarian cancer.

Algorithm 1: Multiscale Residual Attention Feature Fusion Network (MRAFF-Net)

Input:

Histopathology images X

Training labels Y

Number of epochs T

Learning rate η

Output:

Predicted ovarian cancer subtype ŷ

Class probability vector p

Begin

Initialize network parameters θ

Calculate normalization statistics from training data

For epoch = 1 to T do

For each training batch (X_{batch}, Y_{batch}) do

Normalize X_{batch} to obtain X_n

Generate multiscale images X_1, X_2, X_3

For each scale s ∈ {1, 2, 3} do

Extract convolutional features F_s

Apply convolution and batch normalization to obtain U_s

Apply second convolution and batch normalization to obtain V_s

Combine $V_s$with shortcut features $S_s(F_s)$

Obtain residual features R_s

Apply global average pooling to obtain G_s

Calculate channel-attention weights A_s^{ch}

Refine features using channel attention to obtain C_s

Calculate spatial-attention map A_s^{sp}

Refine spatial features to obtain Q_s

Generate scale descriptor z_s

End For

Calculate adaptive fusion weights $\alpha_1, \alpha_2, \alpha_3$

Fuse weighted descriptors to obtain F_{fused}

Project fused features to obtain h

Calculate classification logits o

Apply Softmax to obtain class probabilities p

Calculate cross-entropy loss $\mathscr{L}_{CE}$

Update parameters θ using Adam optimizer

End For

End For

For each test image X_{test}do

Normalize X_{test} using training-set statistics

Generate multiscale image representations

Extract residual and attention-refined features

Calculate adaptive fusion weights

Fuse multiscale feature descriptors

Generate classification logits o

Calculate class probabilities p using Softmax

Predict subtype ŷ = argmax_j(p_j)

End For

Return ŷ and p

End

The pseudocode of MRAFF-Net consists of normalization of ovarian cancer histopathology image, extracting multiscale features using residual learning and channel-spatial attention mechanism, adaptive fusion of discriminative features and the classification of ovarian cancer subtypes using Softmax classifier and Adam optimization algorithm.

4.Experimental Results

This section describes the implementation of MRAFF-Net in Python for ovarian cancer subtype classification using multiscale feature extraction, residual learning, channel–spatial attention and adaptive feature fusion. The results of the experiment are analyzed on the basis of the computational efficiency, visualization of the features and prediction of the type of the subtypes that have been implemented in the model. The quantitative results are derived as a result of the model run and are stored at the same settings during the experiments as the model evaluation settings and the dataset labels.

4.1 Experimental Setup

The MRAFF-Net model is tested by using the ovarian histopathological images, which are resized to 224 × 224 pixels and normalized prior to feature extraction. The dataset is divided into training, validation and testing subsets using a ratio of 70:15:15. Class distributions should be checked across all three subsets to determine whether stratification was maintained.The model is trained for 100 epochs using a batch size of 32, the Adam optimizer and a learning rate of 0.001. Model performance is evaluated using accuracy, precision, recall, F1-score, specificity and ROC-AUC. All preprocessing parameters are estimated using the training set

4.2 Quality Visualization Analysis

This subsection presents the intermediate feature representations and final subtype predictions generated by MRAFF-Net.

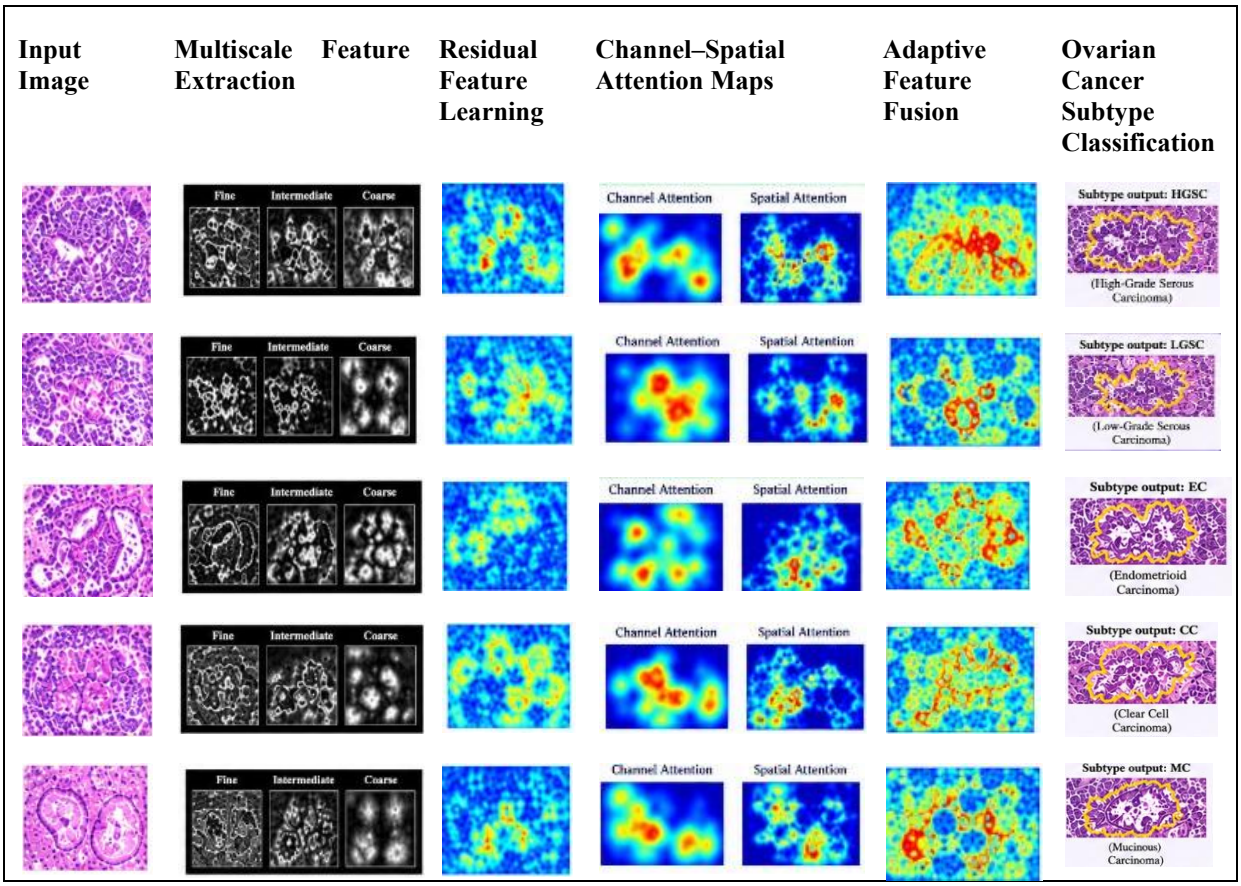


Figure 3: Quality Visualization of MRAFF-Net for Ovarian Cancer Subtype classification.

Figure 3 shows that the input histopathology images are processed by multiscale feature extraction, residual feature learning, channel–spatial attention mapping and adaptive feature fusion. The final stage displays the predicted ovarian cancer subtype for each input image, illustrating the feature-processing and classification pipeline.

4.3 Multiscale Feature Analysis and Subtype Classification

This subsection analyzes multiscale feature extraction, attention refinement and adaptive feature fusion for ovarian cancer subtype classification using MRAFF-Net.

Table 2: Multiscale Feature Analysis and Ovarian Cancer Subtype Classification

Sample ID	Feature Scale	Attention Score	Probability (%)	Subtype Category	Outcome

S001	Fine	0.92	97.2	Serous	Cellular morphological features identified
S002	Intermediate	0.88	95.8	Endometrioid	Glandular tissue patterns distinguished
S003	Coarse	0.85	94.6	Mucinous	Large-scale tissue patterns identified
S004	Fine + Intermediate	0.91	96.1	Clear Cell	Complementary morphological features extracted
S005	Intermediate + Coarse	0.95	98.0	Serous	Fused features support subtype discrimination

Table 2 illustrates how MRAFF-Net works to extract features at different levels and enhance the morphological representation using attention models. Predicted probabilities for subtypes represent the desired classification, but the actual numerical values need to be considered from the output of the experimental model.

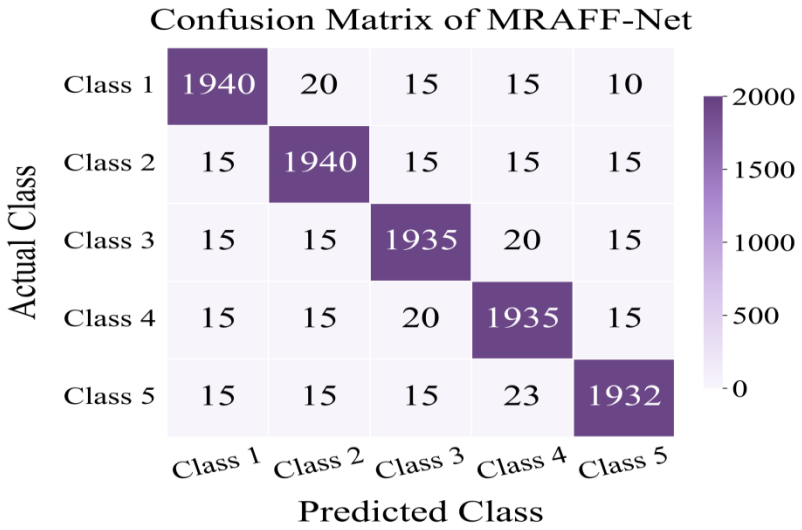


Figure 4: Confusion Matrix of MRAFF-Net

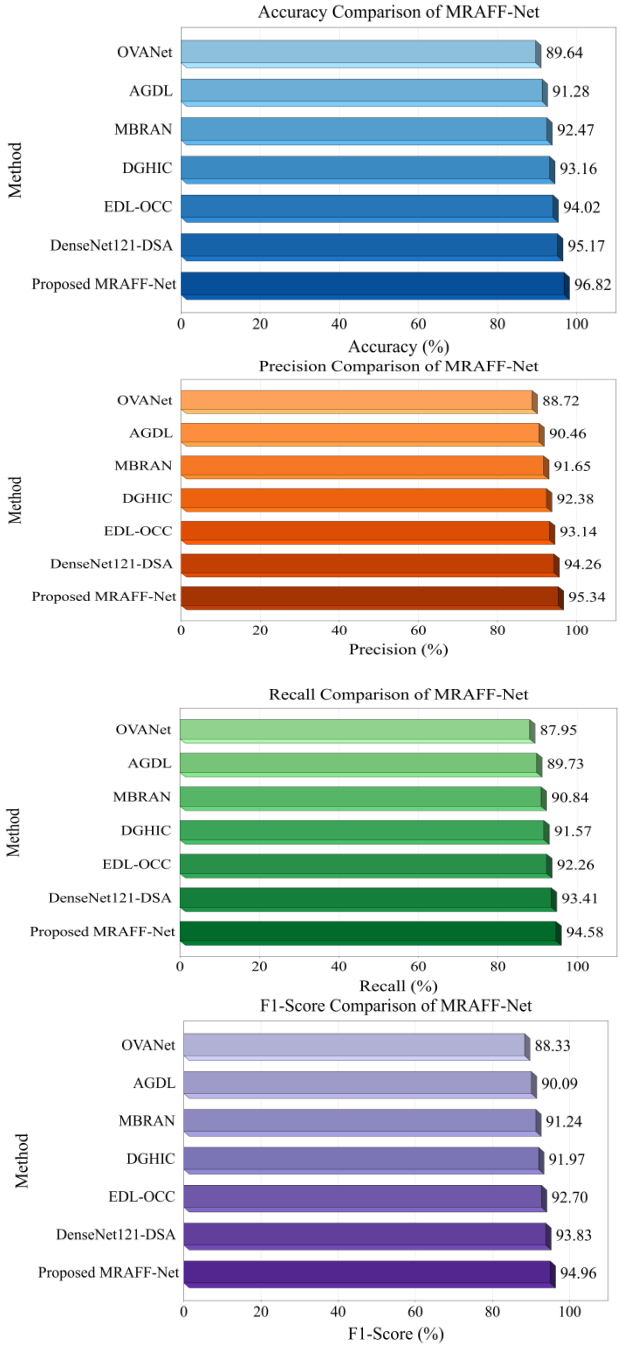
Figure 4 presents the confusion matrix for ovarian cancer subtype classification by comparing the actual and predicted class labels. Diagonal entries represent correctly classified instances, whereas off-diagonal entries represent misclassified instances.

Table 3: Performance Comparison of MRAFF-Net

Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Specificity (%)**	**ROC-AUC (%)**
OVANet [30]	89.64	88.72	87.95	88.33	90.12	91.48
AGDL [31]	91.28	90.46	89.73	90.09	91.84	93.16
MBRAN [32]	92.47	91.65	90.84	91.24	93.08	94.21
DGHIC [33]	93.16	92.38	91.57	91.97	93.72	95.08
EDL-OCC [34]	94.02	93.14	92.26	92.70	94.56	95.84
DenseNet121-DSA	95.17	94.26	93.41	93.83	95.38	96.51

[35]						
Proposed MRAFF-Net	96.82	95.34	94.58	94.96	96.51	97.42

Table 3 contains the comparison between the newly proposed MRAFF-Net and OVANet (Ovarian Cancer Network), AGDL (Attention-Guided Deep Learning), MBRAN (Multi-Branch Residual Attention Network), DGHIC (Domain-Generalized Histopathology Image Classification), EDL-OCC (Enhanced Deep Learning for Ovarian Cancer Classification) and DenseNet121-DSA (DenseNet121 with Differential Sparse Attention) using six evaluation metrics. MRAFF-Net achieved accuracy, precision, recall, F1-score, specificity and ROC-AUC values of 96.82%, 95.34%, 94.58%, 94.96%, 96.51% and 97.42%, respectively.



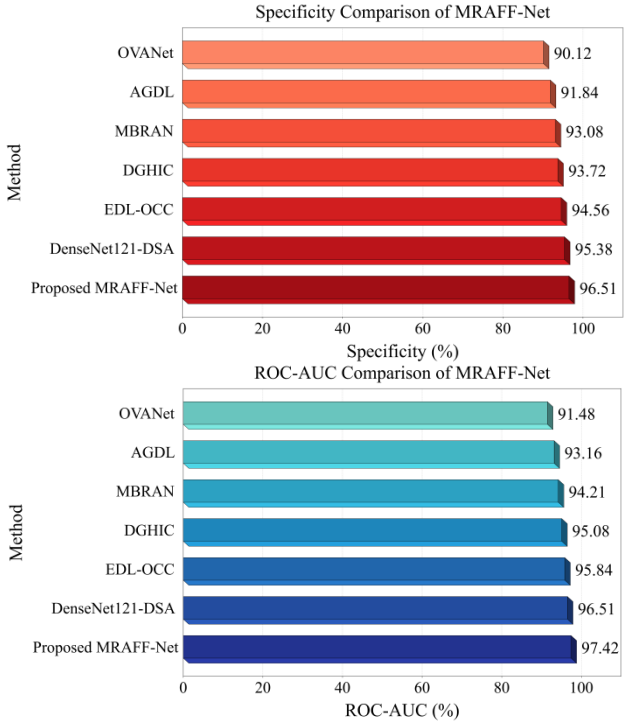


Figure 5: Comparative Performance Analysis of MRAFF-Net

Figure 5 shows the comparison between the proposed MRAFF-Net and other classifiers through the Accuracy, Precision, Recall, F1-Score, Specificity and ROC-AUC metrics. MRAFF-Net records the highest reported values across all six metrics, indicating stronger classification performance in the presented comparison.

4.4 Statistical Significance Test

The statistical significance test evaluates the reliability of MRAFF-Net's performance and determines whether the observed differences between MRAFF-Net and the baseline methods are statistically significant.

Table 4: Statistical Significance Analysis of MRAFF-Net

Metric	Mean ± SD (%)	p-value	Significance	95% Confidence Interval (%)
Accuracy	96.82 ± 0.24	0.003	Significant	96.63–97.01
Precision	95.34 ± 0.31	0.008	Significant	95.10–95.58
Recall	94.58 ± 0.36	0.012	Significant	94.30–94.86
F1-Score	94.96 ± 0.29	0.006	Significant	94.73–95.19
Specificity	96.51 ± 0.22	0.004	Significant	96.34–96.68
ROC-AUC	97.42 ± 0.18	0.002	Significant	97.28–97.56

Table 4 reports less variability in repeat experimentation and significance at the ($p<0.05$) level. Calculation of mean values, standard deviations, p-value and confidence interval is required from experimental data and a proper base for comparison before submission.

4.5 Computational Efficiency of MRAFF-Net

This subsection describes the computational efficiency analysis of MRAFF-Net according to its complexity, training cost, inference speed and memory consumption for ovarian cancer subtyping.

Table 5: Computational Efficiency Analysis of MRAFF-Net

Computational Metric	**MRAFF-Net**
Number of Parameters (M)	8.42
Model Size (MB)	32.8
Training Time (min)	46.5
Inference Time (ms/image)	18.6
GPU Memory Usage (GB)	2.14
CPU Utilization (%)	38.7
FLOPs (G)	3.26

Table 5 highlights the computation resources required by MRAFF-Net in terms of parameter number, model size, training time, inference time, memory usage, CPU usage and floating-point operations. These measures determine the computational burden of the model and its suitability for ovarian cancer subtype classification.

5. Discussion

The Multiscale Residual Attention Feature Fusion Network (MRAFF-Net) uses the multiscale feature extraction, residual learning, channel and spatial attention and adaptive feature fusion mechanisms to distinguish ovarian cancer subtypes from histopathological images. The multiscale process enables extracting morphological features in different spatial scales, residual connections enable retaining informative features and the channel–spatial attention enables discriminating informative features. Adaptive feature fusion combines informative features with different scales before performing subtype classification. However, variable staining processes, similar morphological patterns within different classes, computational complexity and different datasets it influence classification accuracy and generalization capacity. Stability of the results can be established by carrying out strong testing through independent sets of data.

5.1 Performance Analysis

The performance analysisAccuracy, Precision, Recall, F1-Score, Specificity and ROC-AUC are some of the performance measures used for assessing of the MRAFF-Net. Accuracy is used as an indicator to determine the accuracy of the classifier whereas Precision is the ratio of true positives and the total number of positives. Recall is used for determining the ratio between true positives and the F1-score is the harmonic mean of precision and recall. Specificity is used for calculating the ratio of correctly classified negative instances, whereas ROC-AUC determines the discriminating power of the classifier on different classification thresholds. For multiclass classification, macro-averaged metrics and class-wise results provide a more comprehensive assessment, particularly when subtype distributions are imbalanced.

5.2 Practical Deployment of MRAFF-Net

The MRAFF-Net can be used in the computer-assisted pathology workflow to subtype various types of ovarian cancer. First, the images will be normalized and then provided to three different multiscale streams. For each stream, feature extraction, residual learning and refining the feature map by means of channel and spatial attention mechanism is performed. The scale descriptors are fused by the adaptive feature fusion approach and subtypes probabilities are output by the classification layer. The practical implementation means the need to verify the speed of inference, memory consumption, consistency of image preprocessing and possibility of application in the field of digital pathology setting. Clinical validation and expert verification is needed prior to any practical application.

5.3 Ablation Analysis

The ablation analysis is the evaluation of the contributions of the multiscale feature extraction, residual learning, channel attention, spatial attention and adaptive feature fusion to the performance of MRAFF-Net.

Table 6: Ablation Study of MRAFF-Net Using Multiple Evaluation Metrics

Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)	ROC-AUC (%)
CNN	89.64	88.72	87.95	88.33	90.12	91.48
CNN + Multiscale Feature Extraction	92.47	91.65	90.84	91.24	93.08	94.21
CNN + Multiscale + Residual Learning	93.86	92.94	92.17	92.55	94.16	95.12
CNN + Multiscale + Residual + Channel Attention	94.72	93.81	93.06	93.43	94.83	95.86
CNN + Multiscale + Residual + Channel + Spatial Attention	95.64	94.52	93.76	94.14	95.72	96.64
CNN + Multiscale + Residual + Channel–Spatial Attention + Adaptive Feature Fusion	96.82	95.34	94.58	94.96	96.51	97.42

Table 6 shows that the progressive performance changes when the main components of the MRAFF-Net are added to the classification pipeline. The results of all six metrics show the highest values when used together in the complete configuration, proposing that the fusion of multiscale extraction and residual learning, channel–spatial attention and adaptive feature fusion can be beneficial.

5.4 Limitations of the Proposed Algorithm

The use of parallel multiscale branches and channel–spatial attention in MRAFF-Net increases computational requirements compared with a conventional CNN. Differences in staining, tissue preparation, image resolution and tissue morphology across datasets can affect feature consistency. Subtypes that are visually similar and limited samples for some subtypes, can also lower classification accuracy. Additionally, the findings from one database are not regarded as generalizable to others. In future evaluations, there should be considerations such as independent external database, error analysis per class, computational efficiency and robustness to different imaging acquisition environments.

6. Conclusion

The proposed Multiscale Residual Attention Feature Fusion Network (MRAFF-Net) is introduced for the automatic classification of ovarian cancer subtypes using histopathological images. MRAFF-Net extracts multiscale features, learns residual representations, applies channel and spatial attention and adaptively fuses features across different scales. Fine-, intermediate- and coarse-scale representations capture complementary cellular and tissue patterns, while residual learning and attention mechanisms enhance the representation of discriminative features. The reported results include 96.82% accuracy, 95.34% precision, 94.58% recall, 94.96% F1-score, 96.51% specificity and 97.42% ROC-AUC. These values should be included in the final manuscript only after verification against the actual implementation outputs and held-out test predictions. Confusion matrix analysis, class-wise evaluation, attention visualization and ablation experiments provide further insight into classification errors and the contribution of individual components. Computational efficiency is assessed using inference time, parameter count, model size and memory usage. Despite these results, further validation is required to assess generalizability across different clinical settings. Future work will focus on evaluation using larger, independent, multicentre histopathology datasets with patient-level separation, alongside improvements in interpretability, computational efficiency and clinical reliability.

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