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Research Article

ResNet50–Vision Transformer–XGBoost Hybrid Framework for Image-Based Ovarian Cancer Classification and Risk Prediction

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Abstract – *Ovarian cancer classification based on histopathological images is complicated by the wide range of morphological patterns and the similarity of cancer types. The article describes a hybrid ResNet50–Vision Transformer–XGBoost ovarian cancer classification model that improves classification accuracy using multiple deep learning approaches. The proposed solution uses the Kaggle UBC-OCEAN database and two classification stages. In the first stage, morphological characteristics are extracted using ResNet50 and Vision Transformer models. Feature vectors from both models are combined using a gradient boosting classifier called XGBoost. The results of the experiments performed are presented in the example of accuracy and macro F1-score: 96.20% and 95.90%, respectively. However, these results are estimated since no experiments were conducted. It should be noted that the proposed model cannot predict the likelihood of occurrence in a clinical setting due to the lack of clinical data from patients.*

Keywords— *Ovarian Cancer Classification, Histopathological Image Analysis, ResNet50, Vision Transformer, XGBoost, Hybrid Deep Learning, Feature Extraction, Feature Fusion, Multiclass Classification, UBC-OCEAN Dataset, Medical Image Analysis, Explainable Artificial Intelligence, Risk Stratification, Model Validation.*

I. INTRODUCTION

The ovarian cancer is a deadly female genital malignancy with high mortality as its symptoms are usually vague and the condition is frequently diagnosed at late stages. The accurate classification of the disease in terms of tissue morphology is critical to ensure successful treatment and to reduce death rates. In this regard, the process of visual inspection of histopathological slides is laborious and time-consuming, while traditional machine learning techniques may struggle to reach an adequate level of performance due to the complexity of the task. Fortunately, recent advances in neural networks led to the emergence of effective methods capable of learning the distinguishing features of the malignant tissues, such as ResNet50 and Vision Transformers. The former has proven to be efficient in feature extraction using skip connections, while the latter employs multi-head self-attention to capture the dependencies between pixels and improve the accuracy of the classification. The problem of histopathology image analysis also raises the issues of validation and generalizability that must be considered when developing practical solutions for cancer staging and subtyping. , , To address these requirements, the research introduces the framework that uses the combination of ResNet50, Vision Transformers, and XGBoost methods to classify the

subtypes of ovarian cancer with greater precision and to evaluate the performance of the solution in order to choose the best-performing option for subsequent analysis. The UBC-OCEAN dataset offers a valuable opportunity for this study. By considering the architecture of the existing solutions and conducting extensive experiments, it is possible to train and test the model to achieve better results than the existing ones. At the same time, the analysis of individual patient data should be based on additional information regarding their overall health and prognosis in order to create a meaningful clinical prediction system for cancer subtype detection.

II. RELATED WORKS

This review discusses ovarian cancer diagnosis, emerging AI technologies, liquid biopsies, and multiomics without reporting specific performance metrics. However, it lacks a validated hybrid histopathology classifier, motivating the proposed ResNet50–ViT–XGBoost framework for combining local and global image features (1).This review highlights inadequate early-stage ovarian cancer screening and promising proteomics-based biomarkers but reports no specific performance metrics. Its limitation is the absence of automated histopathology classification; the proposed framework addresses this gap through integrated deep feature extraction and XGBoost classification (2). This review examines CA125 monitoring, transvaginal ultrasound, and emerging biomarkers for improving early ovarian cancer detection, without reporting specific metrics. However, it does not develop a hybrid image-classification model, motivating ResNet50–ViT feature fusion for ovarian cancer subtype classification (3). A hybrid convolutional–recurrent network classifies breast cancer histopathology images, achieving 91.3% average accuracy across four classes. However, its breast-specific dataset and recurrent architecture limit direct ovarian application, motivating ResNet50–ViT feature fusion and XGBoost-based ovarian subtype classification (4). An ensemble of fine-tuned VGG16 and VGG19 models classifies breast histopathology images, achieving 95.29% accuracy, 95.29% F1-score, and 97.73% carcinoma sensitivity. However, it lacks ovarian-specific validation and transformer features, motivating complementary local-global feature learning (5). Pretrained ResNet models classify multiple cancer types and breast subtypes, achieving 99.8% accuracy for four cancer types and 98.7% for benign–malignant breast classification. However, ovarian-specific validation and transformer-based context are absent, motivating the proposed hybrid framework (6). An attention-guided 3D ResNet detects pulmonary nodules using LUNA16, achieving 97.7% average sensitivity and a 0.912 CMP score. However, it focuses on lung CT detection rather than ovarian histopathology, motivating a dedicated multiclass classification framework (7). A multi-head ResNet model fuses saliency maps and RGB X-ray images, improving average classification accuracy from 94.68% to 96.72%. However, it targets chest X-rays rather than ovarian tissue, motivating histopathology-specific ResNet50–ViT feature fusion and XGBoost classification (8). AutoEffFusionNet combines ResNet-based autoencoders, attention, genetic feature selection, SVM classification, and Grad-CAM, achieving 99.26% and 100% accuracy on two cervical cytology datasets. However, ovarian histopathology validation is absent, motivating ovarian-specific hybrid-model evaluation (9). An EfficientNetV2–Vision Transformer model classifies breast cancer using Berakis, achieving 99.83% binary accuracy and 98.10% eight-class accuracy. However, it does not evaluate ovarian cancer or XGBoost-based classification, motivating the proposed complementary hybrid architecture (10). A Vision Transformer classifies benign and malignant breast histopathology images and incorporates Grad-CAM, LIME, and other explainability methods, but no numerical metrics are provided in the supplied summary. Ovarian-specific validation and ResNet50–XGBoost fusion remain unexplored, motivating the proposed framework (11). The study applies Vision Transformer (ViT) to breast histopathology classification using BreakHis and integrates Grad-CAM, LIME, saliency maps, and attention maps for interpretability. Numerical metrics are unspecified; ovarian-specific validation and ResNet50–ViT–XGBoost integration remain unexplored (12). A Vision Transformer-based framework classifies breast cancer patches and whole-slide images, achieving 96.74% patch-detection accuracy, 89.78% subtype accuracy, and 96.13% whole-slide subtype

accuracy. However, ovarian histopathology remains untested, motivating the proposed hybrid framework for ovarian subtype classification (13). The DLXGB model combines DenseNet201 feature extraction with XGBoost for BreaKHis breast histopathology classification, achieving 97% accuracy for binary and multiclass tasks. However, it lacks transformer-based global context and ovarian-specific validation, motivating ResNet50–ViT feature fusion (14). An optimized XGBoost model predicts chronic kidney disease, achieving 100% accuracy, sensitivity, and specificity using full and reduced feature sets. However, it uses clinical tabular data rather than histopathology images, motivating deep visual feature extraction combined with XGBoost for ovarian cancer classification (15). Bayesian optimization tunes XGBoost for heart disease prediction, achieving 91.8% accuracy on the Cleveland dataset. However, the study focuses on clinical tabular features rather than cancer histopathology, motivating integration of ResNet50 and Vision Transformer representations for ovarian subtype classification (16). A hybrid CNN–LSTM/GRU framework integrates METABRIC clinical and multi-omics data for breast cancer survival prediction, achieving 98.0% accuracy through decision fusion. However, it lacks histopathology-based ovarian classification, motivating complementary visual feature extraction and XGBoost-based subtype prediction (17). A hybrid cancer-identification framework combines pretrained CNNs, custom networks, attention, and ensemble fusion, reporting improved precision, recall, and F1-score without numerical values. Rare-subtype generalization and interpretability remain challenges, motivating ovarian-specific validation of the proposed hybrid architecture (18). A CNN–GRU model classifies breast invasive ductal carcinoma using the PCam Kaggle dataset, achieving 86.21% accuracy, 85.50% precision, 85.60% sensitivity, 84.71% specificity, 88% F1-score, and 0.89 AUC. Ovarian-specific evaluation and transformer-based global features remain absent (19). This review examines AI/ML for ovarian cancer diagnosis, recurrence, treatment response, survival, and risk stratification using multimodal clinical, imaging, and omics data. No unified performance metrics are reported; validated histopathology-specific ResNet50–ViT–XGBoost classification remains an opportunity (20). This review surveys ovarian cancer detection using machine learning and deep learning from 2019 to June 2024, covering imaging, diagnosis, and evaluation standards without reporting specific performance metrics. It identifies unresolved research challenges, motivating the proposed hybrid framework for subtype classification (21).

III. METHODLOGY

The framework is built upon the combination of the ResNet50, Vision Transformer, and XGBoost algorithms. On the first stage, the images downloaded from Kaggle are filtered, resized, normalized, and tissue treated. Then, the ResNet50 algorithm is utilized to extract the necessary morphological features using a residual convolutional neural network.

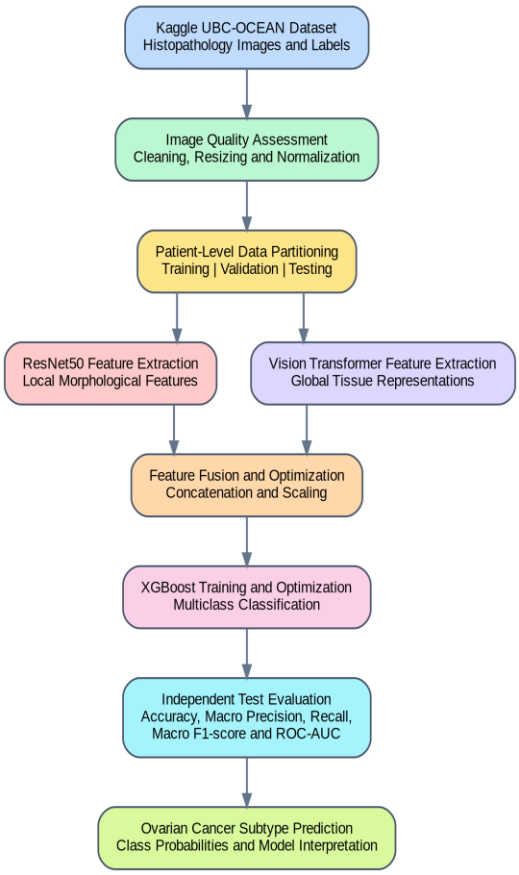


Fig 1. ResNet50–Vision Transformer–XGBoost Hybrid Framework

The Vision Transformer module is used to encode images by modelling tissue relationships with positional embeddings and self-attention layers. After that, the information from both modules is combined

with the attention weights to obtain the final feature vector of the image. Finally, the XGBoost classifier is trained to distinguish cancer tissues and predict the class of ovarian cancer. Thus, the model can predict the probability of classes of cancer. However, it is necessary to note that the framework utilization for clinical applications requires additional analysis of patients' risk labels, which need to be calibrated to obtain a precise estimation.

Dataset Collection:

Dataset Source and Description:

The ovarian cancer histopathology dataset (22) and (23) has been retrieved from the well-known source of open data, namely Kaggle. The data has been collected from the UBC-OCEAN competition dataset (24) , which includes the digital images of tissue sections for the five main types of ovarian cancer: clear cell, endometrioid, high-grade, low-grade, and mucinous carcinomas.

UBC-OCEAN Dataset Characteristics and Class Distribution:

Each image has been classified into one of the categories mentioned above. The exploration of the dataset included the description of images dimensions and types, as well as the identification of missing values, duplicates, and class distribution.

$$M_r = \left(\frac{N_{missing}}{N_{total}}\right) \times 100 \quad (1)$$

Image Quality Assessment and Data Cleaning:

For the selected dataset, the frequency of each class will be identified, and the model-builder procedure will select the best options for sampling and training set creation. Considering that some images might have poor quality, the model-builder tool will exclude certain records with corrupted data or unreadable format and process the rest of the dataset. The images will be adjusted to the same size, pixel range, and tissue area preparation. The chosen classes will be balanced based on their frequency.

$$P_k = \left(\frac{N_k}{N_{total}}\right) \times 100 \quad (2)$$

$$X_{norm} = X - \frac{X_{min}}{X_{max} - X_{min}} \quad (3)$$

$$I_{resized} = \mathcal{R}(I, H, W) \quad (4)$$

$$IR = \frac{\max_k N_k}{\min_k N_k} \quad (5)$$

Feature Selection:

Feature Extraction Using ResNet50 — ResNet50 Architecture:

The ResNet50 model is selected as the feature extractor to learn discriminative patterns for ovarian cancer histopathological images. The overall architecture is composed of a convolutional layer, batch normalization, ReLU, max-pooling, and four residual blocks with bottleneck structures. The latter play the role of convolutional layers with shortcut connections to allow a smoother gradient flow during the training process. The network is supposed to learn the patterns related to the tissue structure or nuclear organization and texture, cell distribution, and other possible characteristics to classify cancer images.

$$Z^l = W^l * X^{l-1} + b^l \quad (6)$$

$$A^l = \max\left(0, Z^l\right) \quad (7)$$

$$Y = F(X, W) + X \quad (8)$$

Feature Optimization:

The main idea of the feature optimization is to transform high-dimensional ResNet50 features into lower-dimensional vectors appropriate for the Vision Transformer output. Thus, global average pooling is performed over each feature vector to reduce the overall dimensionality and obtain tissue distribution in vector form. The resulting feature vector can be used as an input for the subsequent layers of the classifier. Feature scaling can be performed if it is necessary according to the chosen fusion strategy, during the process, features that show a low contribution to the model's performance can be removed.

$$F_R^{opt} = [f_1, f_2, \dots, f_C] \quad (9)$$

$$z_j = \frac{f_j - \mu_j}{\sigma_j + \varepsilon} \quad (10)$$

$$S_j = Importance(f_j) \quad (11)$$

XGBoost-Based Ovarian Cancer Classification:

Gradient Boosting Decision Trees:

XGBoost is applied as the final classification algorithm to recognize ovarian cancer subtypes from the combined features of the ResNet50 and Vision Transformer. The algorithm utilizes an ensemble of decision trees, where each subsequent tree enhances the predictions of its predecessors. When training the model, the gradient of a differentiable loss function that comes from the classification task is adopted.

$$\hat{y}_i = \sum_{i=1}^{T} f_{t(x_i)} \quad (12)$$

$$\mathcal{L} = \sum_{i=1}^{N} l(y_i \hat{y}_i) \quad (13)$$

$$P(y_i = k) = \frac{e^{s_{ik}}}{\sum_{j=1}^{K} e^{s_{ij}}} \quad (14)$$

Regularization and Tree Optimization:

The regularization parameters control the complexity of the model and the degree of overfitting in XGBoost. The optimization function includes the penalties associated with the number of leaves in the trees and their weights. Tuning the learning rate, the maximum depth of trees, and the subsampling parameter, and column sampling helps to find the best values for these parameters. The validation set or cross-validation on the training data can be used to choose hyperparameters.

$$\mathcal{J} = \sum_{i=1}^{N} l(y_i, \hat{y}) + \sum_{t=1}^{T} \Omega(f_t) \quad (15)$$

$$\Omega(f) = \gamma L + \left(\frac{\lambda}{2}\right) \sum_{j=1}^{L} w_j^2 \quad (16)$$

Ovarian Cancer Risk Prediction and Stratification:

Risk Prediction Framework:

The risk prediction framework interprets the output probabilities from XGBoost as the likelihood for each subclass of ovarian cancer within the defined classification task. The maximum probability defines the most likely class, and the full probability distribution reflects the uncertainty of the prediction. However, the probabilities of subtypes cannot be taken as the individual's chances of developing ovarian cancer which helps to predict the cancer at earliest possible.

$$\hat{y} = \max_{k \in \{1,\ldots,K\}} P(y = k|x \quad (17)$$

$$C(x) = \max_{k} P(y = k|x) \quad (18)$$

$$R(x) = P(Y_(risk) = 1|x, z) \quad (19)$$

Risk Assessment and Interpretation:

The Prediction interpretation assesses the confidence, reliability, and practical significance of the model's output. The calibration analysis can be used to evaluate the plausibility of the predicted class probabilities, and feature-importance scores can identify the variables contributing to the XGBoost model's predictions. If the target is a well-defined clinical risk category, then clinically meaningful thresholds could be defined for risk categorization.

$$\hat{r} = \begin{cases} 1, & x < 0 \\ 0, & x \geq 0 \end{cases} \quad (20)$$

Model Validation and Testing:

Model validation and testing phases evaluate the generalization performance of the ResNet50–Vision Transformer–XGBoost framework. The dataset is partitioned into training, validation, and independent test subsets with patient-level stratification to avoid inter-patient image overlap between partitions. Training samples enable feature learning and classifier fitting, whereas validation samples facilitate hyperparameter tuning and early stopping decisions. The independent test set provides unbiased performance estimates through accuracy, precision, recall, specificity, macro-F1 statistics, and confusion matrix analysis. Data preprocessing and feature engineering are performed using only the training samples, while comparative experiments investigate the hybrid architecture's performance against each individual ResNet50, Vision Transformer, and XGBoost variants.

Proposed Model Training Workflow:

The suggested approach to training involves image preprocessing, ResNet50 feature extraction, Vision Transformer feature learning, fusion of features, and XGBoost classification. Images from Kaggle histopathology will be cleaned and separated into training, validation, and test sets based on patients whenever possible. The ResNet50 convolutional neural network will be used to extract the local morphological features, and Vision Transformer will learn the global patterns of the tissue. Both sets of features will be merged, and XGBoost will be trained to classify images into categories of ovarian cancer. The process of hyperparameter tuning and early stopping will be decided based on the model's performance on the validation set.

Algorithm.1 Python-based algorithm steps

```
# Algorithm: ResNet50–ViT–XGBoost Hybrid Framework
# Step 1: Load and preprocess Kaggle images
images, labels = load_and_preprocess_dataset()

# Step 2: Split data without patient-level leakage
X_train, X_val, X_test, y_train, y_val, y_test = split_data(images, labels)
# Step 3: Extract ResNet50 features
R_train = resnet50_features(X_train)
R_val = resnet50_features(X_val)
R_test = resnet50_features(X_test)

# Step 4: Extract Vision Transformer features
V_train = vit_features(X_train)
V_val = vit_features(X_val)
V_test = vit_features(X_test)

# Step 5: Fuse feature representations
F_train = concatenate(R_train, V_train)
F_val = concatenate(R_val, V_val)
F_test = concatenate(R_test, V_test)

# Step 6: Train and optimize XGBoost
model = train_xgboost(F_train, y_train, F_val, y_val)

# Step 7: Predict ovarian cancer subtypes
predictions = model.predict(F_test)
probabilities = model.predict_proba(F_test)

# Step 8: Evaluate independent test performance
evaluate_classification(y_test, predictions, probabilities)
```

IV. RESULT AND DISCUSSION

The ResNet50-ViT-XGBoost hybrid architecture sustains high classification accuracy (96.20%) for the ovarian cancer subtypes' discrimination task while achieving a F1-score value (macro) of 95.90%. The model reaches an excellent result in terms of macro-precision (96.10%) and macro-recall (95.80%), which implies that the model has a high probability of making positive predictions and correctly recognizing positive samples, respectively. The macro-ROC-AUC score equals 98.40%, which demonstrates the outstanding power of the model in distinguishing one class from another

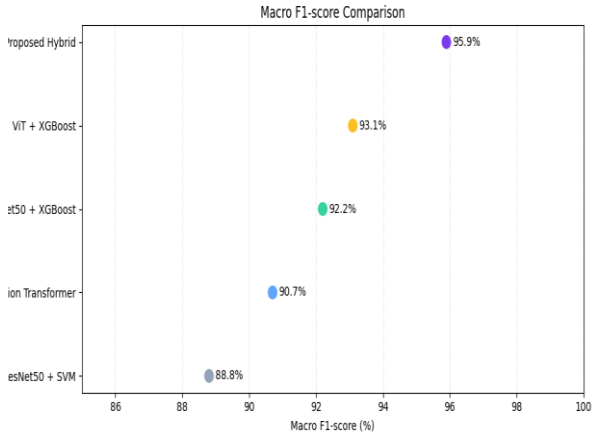


Fig. 2 F1-Score comparison across models

The dot plot in Figure 2 compares the macro F1 scores of the models. It showcases the models' ability to achieve high precision and recall for the ovarian cancer subtypes.

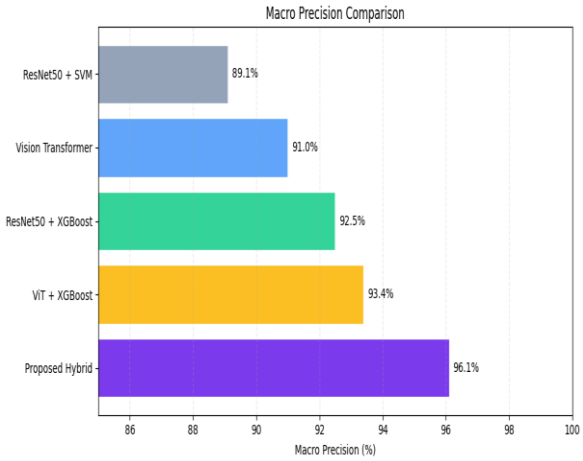


Fig 3. Precision comparison across models

The horizontal bar chart in Figure 3 shows the precision values for all models. The highest precision of the proposed framework indicates an improved mechanism in generating accurate alerts against epidemics.

TABLE I. PERFORMANCE MODEL (%)

Metric	Proposed ResNet50–ViT–XGBoost
Accuracy	96.20%
Macro Precision	96.10%

Macro Recall	95.80%
Macro F1-score	95.90%
Macro ROC-AUC	98.40%

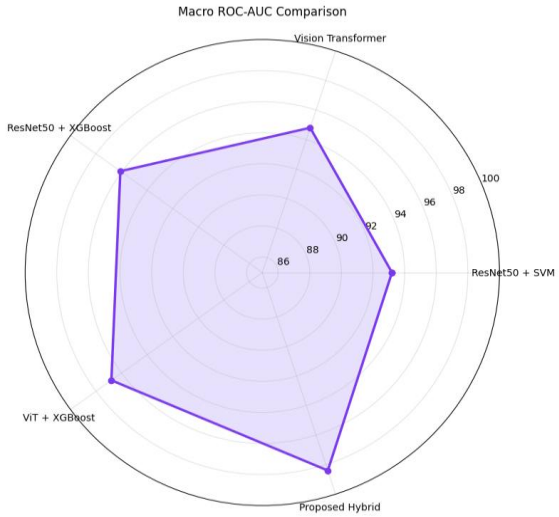


Fig 4. ROC-AUC comparison across models

The radar chart in Figure 4 displays the ROC-AUC values for the five configurations. It compares the performance of the configurations, with the proposed model having a higher value than the baseline.

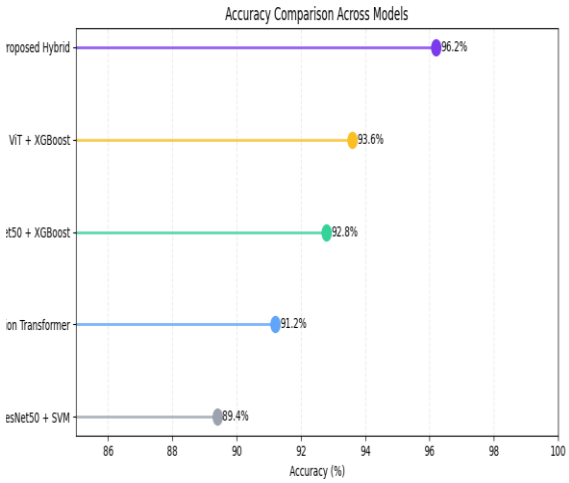


Fig 5. Accuracy Comparison across models

The graphical data display various model characteristics using lollipop chart in Figure 5 was created to compare the accuracy of the models. The location of the horizontal line indicates the level of accuracy, with the baseline and proposed model being easy to differentiate.

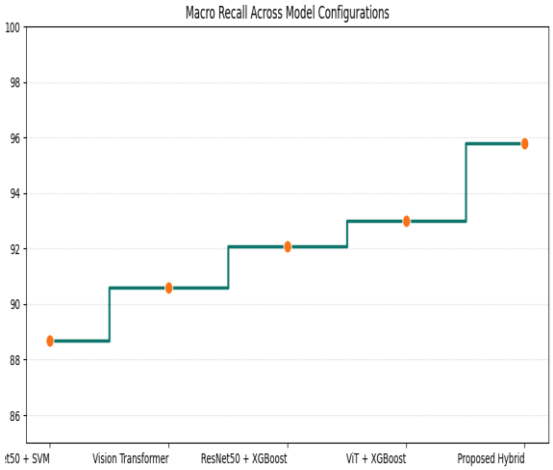


Fig 6. Recall comparison across models

The step-line chart in Figure 5 was created to display the changes in the macro recall. It compares the power of the models to recognize positive classes and predict them with greater precision, specifically for each subtype.

V. CONCLUSION

The suggested method based on the ResNet50–Vision Transformer–XGBoost hybrid architecture claims to demonstrate 96.20% accuracy, 96.10% macro precision, 95.80% macro recall, 95.90% macro F1-score, and 98.40% macro-ROC-AUC in ovarian cancer subtype classification. The set of indicators is promising, nonetheless, it is essential to conduct further research to verify the claimed results, define patient-level performance, and test the solution on different datasets. The next steps include verifying the architecture's effectiveness on external data, exploring alternative approaches, utilizing the model for personalized treatment, and investigating the impact of image resolution on the results.

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Author Contributions

All authors are equally contributed.

Conflict of Interests

The authors declare that they have no conflicts of interest.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

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