Beyond Single Models: Hybrid Approaches for Multiclass Cancer Identification

Kartik A. Gadad
Department of E&C
KLS Gogte Institute of Technology
Belagavi, India
kartikgadad2001@gmail.com

Anil B. Gavade
Department of E&C
KLS Gogte Institute of Technology
Belagavi, India
abgavade@git.edu

Parth V. Patil
Department of Computer Science
KLS Gogte Institute of Technology
Belagavi, India
parthpatil1626@gmail.com

Amey Kurade
Department of E&C
KLS Gogte Institute of Technology
Belagavi, India
ameykurade369@gmail.com

Priyanka R. Patil
Department of E&C
KLS Gogte Institute of Technology
Belagavi, India
priyankarpatil1821@gmail.com

***Abstract*—Digital Whole Slide Image (DWSI) classification, essential for detecting cancerous regions, has advanced through hybrid models. Traditional machine learning (ML) and convolutional neural networks (CNNs) have limitations, prompting the need for more sophisticated strategies. ResNet-50 and DenseNet-121 improve feature extraction in DWSI by capturing intricate patterns. Hybrid models use CNNs to excel in extracting hierarchical features and SVMs using kernels such as linear, RBF, sigmoid and polynomial optimize decision boundaries in high-dimensional spaces, enhancing classification accuracy and generalization. In the Colon dataset, ResNet-50 + SVM (linear kernel) achieves 97% accuracy. For lung classification (3 classes), ResNet-50 + SVM (RBF) and DenseNet-121 + SVM (polynomial) reach 98.3% and 97%, respectively. This demonstrates the shift towards hybrid models, specifically combining CNNs and SVMs with carefully selected kernels, representing a cutting-edge approach in DWSI classification. This approach capitalizes on the strengths of each model component for superior accuracy, robustness, and adaptability across diverse datasets and classification challenges.**

***Index Terms*—Deep Learning, Hybrid Models, CNN Feature Extraction, SVM Classifier, Kernels**

I. Introduction

Lung and colorectal cancers are among the most prevalent globally, with lung cancer being the most common in men and the second in women, and colorectal cancer ranking third in men and second in women, as per the Global Cancer Observatory. Detecting and classifying these cancers using Whole Slide Images (WSI) is challenging for pathologists, who must meticulously examine each slide to identify dark purple-stained cancer cells amidst light pink normal cells. The cancer severity is assessed based on the density of these dark purple areas. Breast cancer is also widespread, primarily affecting women, though it affects 1% of men as well.

Detecting cancer from DWSI is challenging due to asymptomatic early stages, and conventional methods are time-consuming and error-prone, highlighting the need for advanced tools. Effective screening methods like sputum cytology, thoracoscopy, bronchoscopy, and colonoscopy are crucial. DWSI pathology digitizes slides, enabling faster, more accurate analysis and collaboration [6]. AI, particularly DL, shows promise in medical image classification. CNNs like ResNet-50 and DenseNet-121 extract intricate features into vectors for classification. Our models integrate DL and ML, using ResNet-50 for nuanced feature extraction and DenseNet-121 for enhanced propagation shown in Fig.[1]. SVM classification with different kernels (linear, polynomial, sigmoid, RBF) illustrated in Fig.[4] distinguishes between benign and malignant regions in lung, colon, and breast cancer samples. This paper highlights the significance of hybrid models and the impact of varying kernels on classification accuracy.

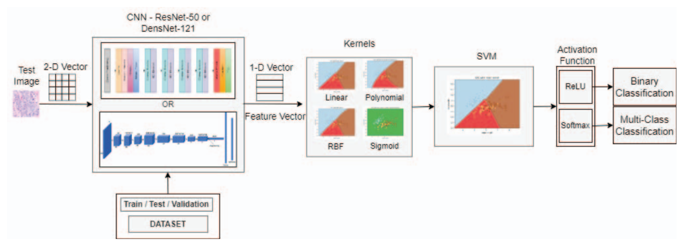

Fig. 1. Overview of our proposed Hybrid SVM model for DWSI

II. Related Work

Extending our previous implementation using ResNet-50 for classification with 98.9% accuracy [8], this paper explores a hybrid SVM-DL model that performs better on wider datasets. Advanced technologies in automated cancer detection have shown promise, particularly with transfer learning architectures. Babu *et al.* [2] utilized transfer learning with a Bayesian optimized SVM classifier, achieving 96.5%-99% accuracy using AlexNet, VGG-16, and Inception-V3. Tasnim *et al.* [21] achieved 99.67% accuracy using MobileNetV2 for colon cell images. Kavitha *et al.* [12] found the SVM model with RBF kernel to be superior for colorectal cancer detection, achieving 91% accuracy compared to 89% with a bare CNN model. Rathore *et al.* [13] also reported 91% accuracy with SVM and RBF kernel for colorectal cancer.In lung cancer research, Keerthana *et al.* [18] achieved 97.91% accuracy with a hybrid CNN-SVM algorithm. Saleh *et al.* [3] achieved 97.53% accuracy using ResNet50 and SVM on the LUNA16 dataset, while Bhatt *et al.* [19] reached 98.57% accuracy using a pretrained ResNet model and SVM. Rajput *et al.* [1] applied PSO, Genetic Optimization, and SVM for lung cancer detection. Asuntha *et al.* [17] conducted a comprehensive survey on colon cancer detection techniques.Transfer learning studies [7], [24] have achieved 96.5%-99% accuracy for colon cancer detection using pre-trained CNNs like AlexNet, VGG-16, and Inception-V3. Studies [5], [10] favored SVM with RBF for colorectal cancer, demonstrating significant accuracy advantages. Corcoran [14] proposed a hybrid CNN-SVM algorithm for lung cancer, achieving 97.91% accuracy. ResNet50 and pretrained ResNet models with SVM achieved 97.53% and 98.57% accuracy in studies [4], [11]. Muhammed Talo [9] integrated PSO, Genetic Optimization, and SVM for lung cancer detection. Bruno Korbar *et al.* [20] provided a comprehensive survey of colon cancer detection techniques.Collectively, research in automated cancer detection, particularly studies [5], [15], [16], [22], and [23], showcases diverse methodologies integrating DL, ML, and image processing techniques, continually advancing the field with innovation and precision.

III. Methods and Materials

A. Dataset Details

This work utilizes the LC25000 dataset, comprising 25,000 histopathological images categorized into five classes from HIPAA-compliant sources. It includes 750 lung tissue images (250 benign, 250 adenocarcinoma, 250 squamous cell carcinoma) and 500 colon tissue images (250 benign, 250 adenocarcinoma). The dataset also features 400 DWSI patches divided into Normal, Benign, InSitu carcinoma, and Invasive carcinoma classes. The images are H&E stained with dimensions of 2048 x 1536 pixels. Class distribution was balanced to prevent biases, enhancing image quality and optimizing crucial attributes.

B. Feature Extraction using CNN

In this study, we use CNNs, specifically ResNet-50 as shown in Fig.[2], for feature extraction from colon, lung, and breast DWSI patches. ResNet-50 consists of an input layer, convolutional layers, pooling layers, and residual blocks. The feature extraction involves convoluting the input image with learnable kernels to produce a feature map, which is then dimensionally reduced by the pooling layer, retaining essential feature information.

In this study, we use CNNs for feature extraction from colon, lung, and breast DWSI patches, focusing on ResNet-50 and DenseNet-121. ResNet-50, with its residual learning blocks and down sampling, enhances gradient flow and reduces spatial dimensions, while its global average pooling ensures fixed-size output. DenseNet-121 features dense blocks

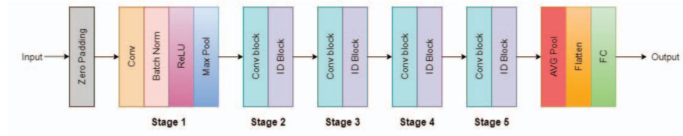

Fig. 2. Architectural Overview and Implemented Summary of ResNet-50 with defined layers for feature extraction

where each layer connects to every other layer, promoting efficient feature extraction and parameter efficiency Fig.[3]. Both architectures include fully connected layers and activation functions (ReLU or Softmax) to produce class probabilities, excelling in image classification tasks.

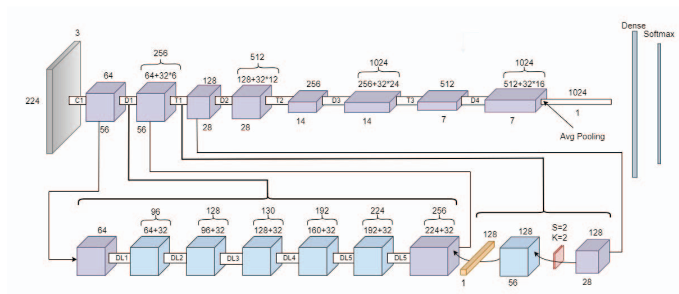

Fig. 3. Architectural Overview and Implemented Summary of ResNet-50 with defined layers for feature extraction

C. Significance of Hyperplane

Hyperplanes are crucial decision parameters for classifying data points, adapting to the dimensionality of features in multi-class problems like lung and breast datasets, where they operate in 2-D and 3-D, respectively. Specifically tailored for non-linear problems, hyperplanes play a pivotal role in effective classification.

D. SVM Kernels

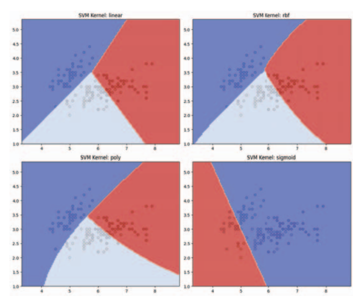

Fig. 4. Classes separation using Kernels: The graph illustrates the conceptual behavior of different kernels. Each kernel exhibits unique characteristics in capturing and classifying complex patterns within the data.

The SVM algorithm aims to find an optimal hyperplane to separate data feature points accurately using the hypothesis function. The hypothesis function $h(x_i)$ is defined as:

$$h(x_i) = \begin{cases} +1 & \text{if } w \cdot x_i + r \geq 0 \\ -1 & \text{if } w \cdot x_i + r < 0 \end{cases}$$

Linear Kernel:

$$K(p_i, p) = p_i \cdot p \tag{1}$$

- Effective in distinguishing between cancerous and non-cancerous colon tissues based on linearly separable features.
- Useful in separating lung cancer data into distinct classes only when features exhibit a linearly separable pattern.

Polynomial Kernel:

$$K(p_i, p) = (p_i \cdot p + a)^b \tag{2}$$

where; a is a constant and b is the degree of the polynomial.

- Applied to capture non-linear relationships in colon cancer datasets, accommodating cases where the decision boundary is more complex.
- Useful for lung cancer classification, capturing complex relationships in the feature space and accommodating non-linear patterns.

Radial Basis Function (RBF) or Gaussian Kernel:

$$K(p_i, p) = \exp\left(-\frac{\|p_i - p\|^2}{2c^2}\right) \tag{3}$$

where; c is the kernel width parameter.

- Well-suited for capturing intricate relationships between features in the high-dimensional space employed when colon cancer data exhibits non-linear patterns.
- Widely used for lung cancer classification, particularly in cases with complex and non-linear relationships between features, enabling the discernment of subtle patterns.

Sigmoid Kernel:

$$K(x, y) = \tanh(a \cdot x^T y + b) \tag{4}$$

where; a is a scaling factor, and b is a constant.

- Applied for handling non-linear separations in colon cancer datasets, providing flexibility in capturing diverse patterns.
- Utilized in lung cancer classification tasks where non-linearities need consideration, offering a versatile approach to capturing intricate relationships between features.

E. Experimental Setup

Experimental Setup Our algorithm was implemented using Python and tensorflow deep learning framework. To support the intricate processes and classification tasks involved, we utilized a powerful computing machine. the **Dell Precision Tower 5810 workstation**, which is equipped with a Xeon CPU, 512 GB SSD, 32 GB RAM, and an 8 GB Quadro P4000 Nvidia GPU. This robust configuration provided the necessary computational power for our implementation.

F. Evaluation Metrics

In medical image classification, the confusion matrix details True Positives, True Negatives, False Positives, and False Negatives to assess predictive accuracy. Precision measures accurate positive predictions, while Recall (Sensitivity) captures all positive instances. The F1 Score balances Precision and Recall. The ROC Curve shows sensitivity versus specificity trade-offs, aiding threshold selection, with the AUC summarizing overall discriminative ability. These metrics collectively inform model evaluation, aiding performance assessment and comparison in medical diagnostics.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \tag{5}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{6}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{7}$$

$$\text{F1-score} = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \tag{8}$$

IV. Results and Discussion

In this section, we comprehensively compare Hybrid ResNet50+SVM and DenseNet121+SVM models on colon, lung, and breast datasets. We emphasize kernel selection relevance and demonstrate hybrid model superiority highlighting procedural efficiencies and kernel specificity.

A. Results for Colon, Lung and Breast Cancer Classification using ResNet-50 and SVM model

ResNet-50 extracts features from patches, forming a vector used by SVM for cancer type classification. Kernel selection in SVM and feature type are critical to classification in this hybrid study across binary and multi-classes.

1) Classification of Colon Cancer using Hybrid ResNet-50 + SVM Model: The hybrid ResNet-50+SVM model significantly outperformed the SVM model alone. In binary classification for the colon dataset, the linear kernel achieved superior accuracy, precision, recall, and F1 scores. [I]. Through extensive experimentation on a robust dataset of 10,000 colon cancer samples, our approach achieves remarkable results: ResNet-50 exhibits 97% accuracy, 98.91% precision, 94.79% recall, and a 96.8% F1 score. DenseNet-121 achieves 98% accuracy, 97.7% precision, 97.79% recall, and a 97% F1 score. The choice of SVM kernels plays a critical role in classification accuracy.

2) Classification of Lung Cancer using Hybrid ResNet-50 + SVM Model: Using the lung dataset, the hybrid model exhibited superior training performance and delivered significant results, particularly with the linear kernel achieving the highest evaluation metrics. [II] In our study of a robust dataset containing 15,000 lung cancer samples, our approach achieved outstanding results due to the dataset's linear separability. Using ResNet-50, we obtained an accuracy of 97%, precision of

TABLE I
PERFORMANCE OF SVM KERNELS ON THE COLON DATASET

Kernels	Accuracy	Precision	Recall	F1 Score
RBF	94.38%	93.89%	94.38%	94.27%
Linear	**96.55%**	**96.12%**	**96.55%**	**96.02%**
Polynomial	89.07%	88.56%	89.07%	88.89%
Sigmoid	94.34%	93.95%	94.34%	93.66%

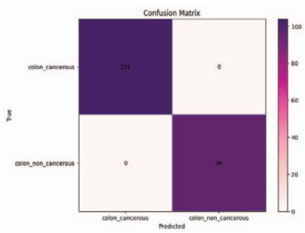

Fig. 5. Confusion matrix for the Linear kernel on Colon Dataset

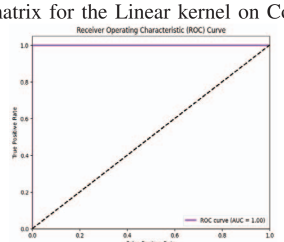

Fig. 6. Confusion Matrix & ROC curve for the Linear kernel on Colon Dataset

98.91%, recall of 94.79%, and F1 score of 96.8%. DenseNet-121 demonstrated even higher performance with an accuracy of 98%, precision of 97.7%, recall of 97.79%, and F1 score of 97%. The choice of SVM kernels significantly influenced our classification accuracy. ResNet-50 benefited from polynomial and linear kernels, while DenseNet-121 excelled with RBF, polynomial, and linear kernels, illustrating effective class separations.

TABLE II
PERFORMANCE OF SVM KERNELS ON THE LUNG DATASET

Kernels	Accuracy	Precision	Recall	F1 Score
RBF	95.00%	95.02%	95.00%	95.01%
Linear	**96.00%**	**96.04%**	**96.00%**	**96.07%**
Polynomial	95.33%	95.34%	95.33%	95.31%
Sigmoid	95.00%	95.02%	95.00%	95.01%

3) Classification of Breast Cancer using ResNet-50 + SVM Model: This highlights significant implications, especially given the dataset's smaller size compared to those used in colon and lung cancer analyses. Despite the challenges posed by this smaller dataset, applying the Hybrid ResNet-50+SVM model yielded noteworthy results. Experimental outcomes demonstrate that using a linear SVM kernel emerged as the optimal choice, achieving the highest accuracy. [III]. This outcome underscores the robustness and versatility of our

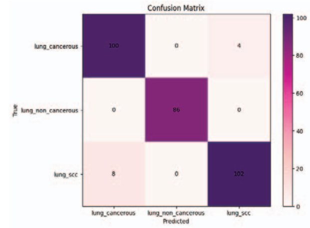

Fig. 7. Confusion matrix for the Linear kernel on Lung Dataset

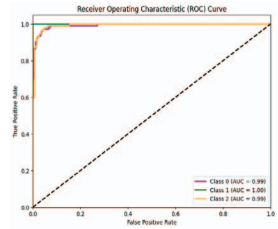

Fig. 8. ROC curve for the Linear kernel on Lung Dataset

proposed model architecture, capable of delivering superior performance despite data scarcity. The effectiveness of the linear kernel emphasizes the inherent linear separability of the breast cancer dataset used. This observation reaffirms both the efficacy of our chosen model architecture and the distinct characteristics of breast cancer data favoring linear classification.

TABLE III
PERFORMANCE OF SVM KERNELS ON THE BREAST DATASET

Kernels	Accuracy	Precision	Recall	F1 Score
RBF	81.25%	82.55	81.25%	82.85%
Linear	**82.50%**	**83.41%**	**82.50%**	**83.54%**
Polynomial	77.50%	78.32%	77.50%	78.30%
Sigmoid	77.50%	78.32%	77.50%	78.30%

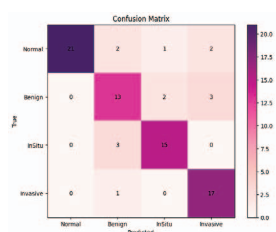

Fig. 9. Confusion matrix for the Linear kernel on Breast Dataset

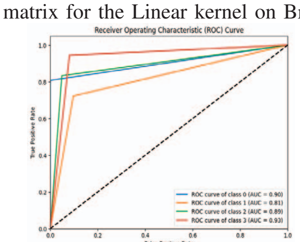

Fig. 10. ROC curve for the Linear kernel on Breast Dataset

B. Results for Colon, Lung and Breast Cancer Classification using DenseNet-121 + SVM Model

The DenseNet-121 architecture extracts features from patches and channels them into SVM kernels for training. Its dense skip connections enhance feature mapping continuity compared to standard skip connections, leveraging previous layer data for richer feature representation. Concatenation mitigates data flow issues across its 121 layers, ensuring seamless information and gradient transmission.

1) Classification of Colon Cancer using DenseNet-121 + SVM Model: Using the Hybrid DenseNet-121 + SVM model, the results obtained are very similar to those of the ResNet-50 model [IV]. The Linear kernel showed slightly better results than others. Other kernels significantly gave better metrics than the Hybrid ResNet-50 + SVM model.

TABLE IV
PERFORMANCE OF SVM KERNELS ON THE COLON DATASET

Kernels	Accuracy	Precision	Recall	F1 Score
RBF	94.38%	93.89%	94.38%	94.27%
Linear	**96.55**%	**96.12**%	**96.55**%	**96.02**%
Polynomial	89.07%	88.56%	89.07%	88.89%
Sigmoid	94.34%	93.95%	94.34%	93.66%

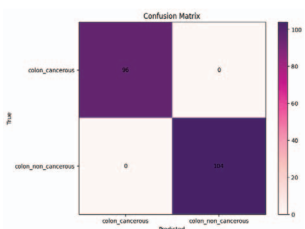

Fig. 11. Confusion matrix for the Linear kernel on Colon Dataset

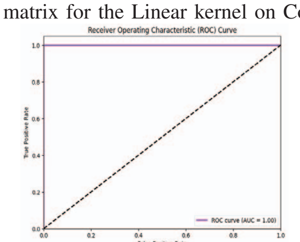

Fig. 12. ROC curve for the Linear kernel on Colon Dataset

2) Classification of Lung Cancer using DenseNet-121 + SVM Model: The DenseNet-121 model applied to the lung cancer dataset outperformed the ResNet-50 model significantly. Through rigorous experimentation, DenseNet-121 exhibited clear advantages, showing enhanced performance across multiple evaluation criteria. The use of linear kernels proved slightly superior to other kernel functions. DenseNet-121's effectiveness in capturing intricate features and patterns within the lung cancer dataset contributed to its superior performance, highlighting the model's capability to discern subtle nuances across its 121 layers. [V].

TABLE V
PERFORMANCE OF SVM KERNELS ON THE LUNG DATASET

Kernels	Accuracy	Precision	Recall	F1 Score
RBF	94.66%	94.84%	94.66%	94.66%
Linear	**95.33**%	**95.38**%	**95.38**%	**95.34**%
Polynomial	94.33%	94.55%	94.33%	94.32%
Sigmoid	95.00%	95.14%	95.00%	94.99%

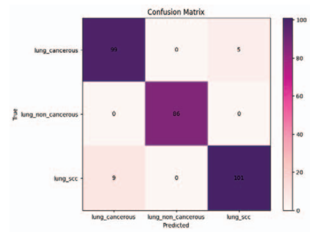

Fig. 13. Confusion matrix for the Linear kernel on Lung Dataset

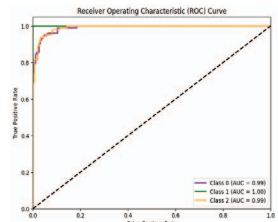

Fig. 14. ROC curve for the Linear kernel on Lung Dataset

3) Classification of Breast Cancer using DenseNet-121 + SVM Model: The results obtained by using the breast dataset on the Hybrid DenseNet-121 + SVM model gave the highest metrics and show significantly how it has a better edge over the Hybrid ResNet-50 + SVM model. It also gave the highest metric employing a linear kernel; the RBF kernel too gave close results, giving competitive results. [VI].

TABLE VI
PERFORMANCE OF SVM KERNELS ON THE BREAST DATASET

Kernels	Accuracy	Precision	Recall	F1 Score
RBF	81.20%	82.44%	81.20%	82.70%
Linear	**82.65**%	**84.00**%	**82.65**%	**84.23**%
Polynomial	78.66%	78.88%	78.66%	78.49%
Sigmoid	77.66%	78.88%	77.66%	78.50%

V. CONCLUSION & FUTURE SCOPE

This study introduces a novel hybrid methodology, integrating ResNet-50 and DenseNet-121 CNNs for feature extraction, complemented by an SVM classifier using diverse kernel functions. Achieving 97% accuracy in colon cancer and 98% in lung cancer classification, the model excels in distinguishing between benign and malignant regions. The meticulous selection of SVM kernels tailored to ResNet-50 and DenseNet-121 features underscores the significance of

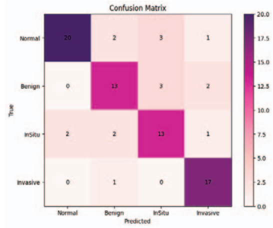

Fig. 15. Confusion matrix for the Linear kernel on Breast Dataset

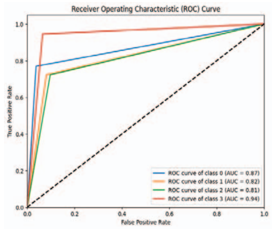

Fig. 16. ROC curve for the Linear kernel on Breast Dataset

our multi-kernel approach. This innovative fusion of DL and SVM shows promise for advancing cancer diagnosis, offering precise tools for early detection and treatment planning in clinical pathology.

Our future research aims to advance cancer detection and classification, focusing on enhancing therapy planning. Exploring advanced kernel functions aims to boost classification accuracy and diagnostic capabilities. Extending evaluations across diverse datasets covering multiple cancer types will showcase the algorithm's adaptability. Additionally, leveraging transfer learning with deep learning architectures like RNNs, LSTMs, and transformers holds promise for future cancer diagnosis advancements.

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