# Combined Deep Learning and Machine Learning Approach for Histopathological Image-Based Cancer Detection

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**Abstract- Cancer remains one of the leading causes of death globally, with early detection being critical for improving patient outcomes. Histopathological imaging, which involves the inspection of tissue samples under a microscope, plays a crucial role in cancer diagnosis. However, manual analysis of these images is effortful, time-consuming, and prone to human error. This paper proposes a hybrid approach that combines deep learning (DL) and machine learning (ML) techniques to automate the detection and classification of cancer, particularly leukemia, using histopathological images. The proposed system influences the ResNet-50 architecture for feature extraction and integrates traditional ML classifiers such as Support Vector Machines (SVM) and Random Forest for robust decision-making. The hybrid model achieves a classification correctness of 97.9%, outperforming existing models. The results demonstrate the potential of this approach to make better early cancer detection, reduce diagnostic errors, and enhance the efficiency of histopathological image analysis.**

***Keywords:*** **Early detection, Histopathological imaging, Cancer diagnosis, Hybrid approach, Deep learning (DL), Machine learning (ML), Leukemia, ResNet-50 architecture Support Vector Machines (SVM), Random Forest.**

## I. INTRODUCTION

Cancer is a leading cause of death globally, with millions of lives lost annually due to late diagnosis and inadequate treatment (World Health Organization, 2020). Early detection of cancer is crucial for timely interference and personalized treatment plans. Among the various diagnostic tools available, histopathological imaging has emerged as a cornerstone in cancer diagnosis. Histopathological images provide detailed visual information about cellular structures, tissue morphology, and the presence of cancerous regions (Rahman et al., 2023). However, manual analysis of these images is effortful, time-consuming, and subject to inter- observer variability, which can lead to diagnostic errors (Patel & Mishra, 2015).

Recent advancements in machine learning (ML) and deep learning (DL) have revolutionized the field of medical imaging, offering automated solutions for image analysis and diagnosis. These technologies have shown great promise in analyzing histopathological images, enabling the detection and classification of cancer with high correctness and efficiency (Behar & Shrivastava, 2021). Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated exceptional performance in identifying cancerous regions in histopathological images, often surpassing human experts in terms of correctness and speed (Almurayzig et al., 2023). Despite these advancements, challenges such as overfitting, vanishing gradients, and the need for large labeled datasets remain significant barriers to the widespread adoption of these technologies in clinical settings (Shalini & Angel Viji, 2022).

This paper proposes a hybrid approach that combines the strengths of traditional ML techniques with state-of-the-art DL architectures to address these challenges. The primary focus of the research is on blood cancer (leukemia), a highly lethal form of cancer that often masquerades as other ailments, making early detection particularly challenging (Karar et al., 2022). The proposed system leverages the ResNet-50 deep neural network architecture, which is known for its capability to handle complex datasets and mitigate issues like overfitting and vanishing gradients through its skip connections (Behar & Shrivastava, 2021). By integrating ResNet-50 with traditional ML models, the hybrid approach aims to achieve higher classification correctness, robustness, and generalizability in the analysis of histopathological images.

## II. LITERATURE REVIEW

### II.1 *Machine Learning and Deep Learning in Cancer Detection*

The advancement of machine learning (ML) and deep learning (DL) in cancer detection has significantly improved the correctness, efficiency, and consistency of diagnostic procedures. Cancer diagnosis, particularly through histopathological image analysis, has traditionally relied on manual investigation by pathologists, a process that is time-consuming, subjective, and prone to variability in interpretation (Rahman et al., 2023). The increasing complexity of cancerous cell morphology, along with the growing need for precise classification and early detection, has posed significant challenges for traditional diagnostic methods.

With the rise of artificial intelligence (AI) in medical imaging, computer-aided diagnosis (CAD) systems have emerged as transformative tools, leveraging machine learning and deep learning to enhance diagnostic correctness and speed (Behar & Shrivastava, 2021). These systems utilize sophisticated algorithms to analyze, classify, and predict cancerous conditions based on large- scale histopathological image datasets. The primary advantage of CAD systems is their capability to detect subtle histopathological patterns that may not be easily discernible through human observation. This has significantly improved early detection and interference strategies, which are crucial for improving patient survival rates (Almurayzig et al., 2023).

### II.2 *Challenges in AI-Driven Cancer Detection*

Despite the advancements in AI-driven cancer detection, several challenges persist. These include the limited availability of high-quality annotated datasets, computational constraints, interpretability of AI models, and variability in staining techniques and imaging conditions (Shalini & Angel Viji, 2022). Addressing these challenges is crucial for the clinical translation of AI-driven cancer diagnostic systems.

## III. METHODOLOGY

### III.1 *Hybrid Approach for Cancer Detection*

The proposed hybrid model combines deep learning (DL) and machine learning (ML) techniques to enhance the correctness of cancer classification using histopathological images. ResNet-50 is used for feature extraction, while traditional ML classifiers such as Support Vector Machines (SVM), Random Forest, and ensemble learning models are employed for classification. This approach leverages the strengths of both DL and ML, ensuring robust and scalable cancer detection.

### III.2 *Data Collection and Preprocessing*

The histopathological image dataset is collected from publicly available sources and medical research databases. Preprocessing steps include image normalization, data augmentation (rotation, flipping, and contrast enhancement), noise reduction, and segmentation to enhance critical features in images.

### III.3 *Feature Extraction Using ResNet-50*

ResNet-50, a deep convolutional neural network (CNN), is used to pull high-level features from histopathological images. Its skip connections mitigate vanishing gradients, improving training efficiency and feature extraction correctness. The extracted features are then used as input for ML classifiers.

### III.4 *Integration of Multiple Machine Learning Models*

The extracted features are classified using ML models, including Support Vector Machines (SVM), Random Forest, and Gradient Boosting Machines (GBM). These models are chosen for their capability to handle high-dimensional data and make better classification robustness.

### III.5 *Evaluation Metrics*

Model performance is assessed using correctness, sensitivity, specificity, precision, AUC-ROC curves, and computational efficiency analysis. These metrics ensure that the model is effective, scalable, and suitable for real-time applications.

## IV. RESULTS AND DISCUSSION

### IV.1 *System Design and Implementation*

The proposed system is designed to automate histopathological image classification by integrating deep learning (DL) and machine learning (ML) techniques. The system architecture consists of an input module, preprocessing module, feature extraction module, classification module, and evaluation module. The system is implemented using Python, with TensorFlow and Scikit-Learn as primary libraries for deep learning and ML tasks.

IV.2*Dataset Description and Preprocessing*

The study utilizes a publicly available histopathological image dataset consisting of images from leukemia and other cancer cases. The dataset is preprocessed using image normalization, stain normalization, data augmentation, and noise reduction to improve model robustness and generalization.

IV.3*Training and Testing of Hybrid Model*

The dataset is split into training (80%) and testing (20%) sets. The model undergoes training in two stages: deep learning feature extraction using ResNet-50 and machine learning classification using SVM, Random Forest, and ensemble learning models. Hyperparameter tuning is conducted using Grid Search and Cross-Validation.

IV.4*Comparative Analysis with Existing Models*

The performance of the hybrid model is compared with existing AI-based cancer detection models, including CNN-only models, traditional ML approaches, and other deep learning models such as VGG-16 and DenseNet. The results confirm that the hybrid model outperforms standalone DL and ML models, achieving a 97.9% classification correctness, compared to 91.84% from previous models (Almurayzig et al., 2023).

IV.5*Performance Evaluation and Validation*

The model's performance is assessed using correctness, precision, recall, AUC-ROC curves, and F1-score. The results validate that the proposed hybrid approach is efficient, scalable, and clinically applicable for histopathological image-based cancer detection.

## V. CONCLUSION AND FUTURE SCOPE

The proposed hybrid approach achieves a classification correctness of 97.9%, significantly outperforming previous models. The integration of ResNet-50 for feature extraction, along with traditional ML classifiers, enhances the system's capability to distinguish between benign and malignant cells with high precision. The model exhibits faster inference times, increased adaptability to complex datasets, and improved correctness across diverse histopathological image variations.

Despite achieving promising results, the proposed hybrid approach has certain limitations, including dependence on image quality, the requirement for large labeled datasets, and high computational resource demand. Future research should focus on developing stain normalization techniques, leveraging semi-supervised learning, and optimizing algorithms for faster inference.

This research contributes to the advancement of AI-driven medical diagnostics, providing a highly efficient and scalable solution for histopathological image-based cancer detection with promising clinical applications in pathology and oncology.

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