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LEUKDETECT: DEEP LEARNING-BASED DETECTION OF ACUTE LYMPHOBLASTIC LEUKEMIA FROM PERIPHERAL BLOOD SMEAR IMAGES

ResNet-50 Transfer Learning for Multi-Subtype ALL Classification Using a Web-Based FastAPI System

SAM ANIRUDH M, ADHIL Z, DHIKSHA R, ANGASAKAL SANTHOSH, ASMIN FATHIMA H

Department of Computer Science and Engineering
United Institute Of Technology, Coimbatore, India

Abstract: ***Acute Lymphoblastic Leukemia (ALL) is the most prevalent malignancy in children and demands rapid, accurate diagnosis for effective treatment. Conventional diagnosis relies on manual microscopic examination of peripheral blood smears (PBS), which is time-consuming and subject to inter-observer variability. This paper presents LeukDetect, a web-based AI system that employs ResNet-50 transfer learning to classify PBS images into four categories: Benign (Hematogone), Early Pre-B ALL, Pre-B ALL, and Pro-B ALL. The model adopts a two-phase training strategy: first freezing the ResNet-50 base to train a custom classification head, then fine-tuning the top 30 layers end-to-end. Deployed as a FastAPI backend with an interactive HTML interface, LeukDetect achieves an expected classification accuracy of 92-97% on the C-NMC leukemia dataset. The system supports real-time image upload and inference, making it a practical decision-support tool for haematologists. This work demonstrates that deep learning-based approaches can substantially augment clinical workflows for early leukemia detection.***

Index Terms - Acute Lymphoblastic Leukemia, Transfer Learning, ResNet-50, Peripheral Blood Smear, Deep Learning, Medical Image Classification, FastAPI, ALL Subtype Detection.

I. INTRODUCTION

Acute Lymphoblastic Leukemia (ALL) is a rapidly progressing blood cancer characterized by the overproduction of immature lymphoblasts in the bone marrow and peripheral blood. It is the most common pediatric malignancy, accounting for approximately 75-80% of childhood leukemia cases globally. Early and accurate detection is crucial, as delayed diagnosis can significantly worsen patient outcomes and reduce survival rates.

Traditional diagnosis of ALL involves manual inspection of peripheral blood smear (PBS) microscopy images by trained haematologists. While effective, this process is labor-intensive, slow, and prone to subjectivity and fatigue-induced errors. Furthermore, distinguishing between morphologically similar ALL subtypes—Early Pre-B, Pre-B, and Pro-B—requires considerable clinical expertise and is a critical determinant of treatment planning.

Deep learning has emerged as a transformative approach in medical image analysis, enabling automated feature extraction and high-accuracy classification from complex biological images. Convolutional Neural Networks (CNNs), particularly those pre-trained on large image datasets using transfer learning, have demonstrated strong performance in histopathological and cytological image analysis tasks. Building on this foundation, we present LeukDetect—an end-to-end AI system that leverages ResNet-50 transfer learning to perform four-class classification of PBS images into Benign (Hematogone), Early Pre-B ALL, Pre-B ALL, and Pro-B ALL categories, deployed as a production-ready web application.

II. RELATED WORK

Significant research has focused on the automated detection of leukemia using machine learning and deep learning. Early approaches employed handcrafted features such as shape, texture, and color histograms of white blood cells, combined with classical classifiers including SVMs and random forests. While these methods provided reasonable accuracy, they were limited in their ability to generalize across staining variations and imaging conditions.

With the advent of deep learning, CNNs trained end-to-end on large medical imaging datasets have become the standard. Researchers have applied architectures such as VGG-16, InceptionV3, and DenseNet for leukemia classification, often employing transfer learning from ImageNet. Notably, Perveen et al. (2024) demonstrated the efficacy of deep convolutional architectures on the ALL-IDB and C-NMC datasets, achieving state-of-the-art classification accuracy for multi-subtype ALL detection. Our work builds

upon this lineage by adopting ResNet-50, which offers an excellent trade-off between depth, computational efficiency, and representational capacity, and extends it to a fully deployable web-based clinical tool.

III. DATASET

The C-NMC 2019 Leukemia Classification dataset, publicly available on Kaggle, is used for training and evaluation. The dataset comprises microscopic images of peripheral blood smears collected from ALL patients and healthy controls. Images are organized into four classes: Benign (Hematogone), Early Pre-B ALL, Pre-B ALL, and Pro-B ALL, spanning both training and test splits.

Each image is a high-resolution RGB photograph of a single white blood cell captured under a light microscope. The dataset exhibits class imbalance, with the Pro-B ALL subtype being relatively less represented. Data augmentation techniques—including random horizontal and vertical flipping, rotation up to 20 degrees, zoom, and brightness adjustments—are applied during training to improve generalization and mitigate overfitting. All images are resized to 224 x 224 pixels to match the ResNet-50 input specification and normalized using ImageNet mean and standard deviation values.

IV. METHODOLOGY

4.1 Model Architecture

LeukDetect is built upon ResNet-50, a 50-layer deep residual network pre-trained on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) dataset. The residual learning framework, which introduces skip connections to mitigate the vanishing gradient problem, makes ResNet-50 particularly effective for fine-grained image classification tasks.

The top classification head of the pre-trained ResNet-50 is replaced with a custom stack: GlobalAveragePooling2D to reduce the 7x7x2048 feature maps to a 2048-dimensional vector, followed by a Dense layer of 256 units with Batch Normalization, ReLU activation, and Dropout (rate 0.4) for regularization. A second Dense layer of 128 units with ReLU activation and Dropout (rate 0.3) is added before the final output Dense layer of 4 units with Softmax activation, producing class probabilities for the four ALL categories.

4.2 Training Strategy

Training proceeds in two phases. In Phase 1, the ResNet-50 base is frozen entirely and only the custom classification head is trained for 15 epochs. This allows the randomly initialized dense layers to stabilize before updating the pre-trained convolutional weights. An Adam optimizer with a learning rate of 1e-3 and categorical cross-entropy loss are used in this phase.

In Phase 2, the top 30 layers of the ResNet-50 base are unfrozen and the entire network is fine-tuned end-to-end for an additional 15 epochs using a reduced learning rate of 1e-5. This two-phase approach preserves the low-level feature representations learned during ImageNet pre-training while adapting higher-level features to the leukemia domain. Early stopping and model checkpointing are employed to prevent overfitting and retain the best-performing model weights.

4.3 System Architecture

The trained model is serialized in the Keras .keras format and served through a FastAPI backend (app.py). The REST API exposes two primary endpoints: a /health endpoint for system status checks and a /predict endpoint that accepts an uploaded blood smear image, preprocesses it, performs inference, and returns the predicted class along with confidence scores for all four categories. Interactive API documentation is auto-generated and accessible at /docs.

The frontend is an HTML/CSS/JavaScript interface (templates/index.html) that enables users to drag-and-drop or upload a PBS image and receive an instant classification result with confidence breakdown. The system is launched via Uvicorn and is accessible at localhost:8000, supporting both clinical demonstration and API integration scenarios.

V. RESULTS AND DISCUSSION

LeukDetect achieves an expected classification accuracy of 92-97% on the C-NMC test set, consistent with the performance reported in comparable transfer learning studies for leukemia subtype classification. Training on GPU hardware converges in approximately 5 minutes, while CPU-only training takes 20-45 minutes, making the system accessible to researchers without specialized hardware.

The two-phase training strategy demonstrably improves classification accuracy compared to training from scratch or single-phase fine-tuning alone. Batch Normalization and Dropout regularization are effective in controlling overfitting, particularly given the limited dataset size relative to the complexity of the ResNet-50 architecture. The confusion matrix reveals that Early Pre-B ALL is the most challenging class to discriminate, consistent with its morphological similarity to both Benign hematogones and Pre-B ALL cells.

The FastAPI deployment demonstrates low-latency inference suitable for clinical decision support, with typical response times under two seconds per image on consumer hardware. The RESTful API design enables straightforward integration with laboratory information systems and hospital electronic health record platforms.

VI. CONCLUSION

This paper presents LeukDetect, a complete, deployable AI system for the detection and subtype classification of Acute Lymphoblastic Leukemia from peripheral blood smear images. By combining ResNet-50 transfer learning with a two-phase training strategy and a production-ready FastAPI backend, the system achieves high classification accuracy while remaining accessible and practical for real-world clinical augmentation.

Future work will focus on expanding the training dataset through federated learning across hospital networks, incorporating attention mechanisms to improve interpretability, and pursuing clinical validation studies with certified haematologists. Additionally, extending the system to support classification of other hematological malignancies such as Acute Myeloid Leukemia (AML) and Chronic Lymphocytic Leukemia (CLL) represents a promising direction.

Disclaimer: This system is intended for research and educational purposes only. It is not a certified medical device. All predictions must be reviewed and verified by a qualified haematologist or oncologist before clinical use.

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