

Pimpri Chinchwad College of Engineering

(Academic Year: 2024-25)

Formative Assessment - 2   
Deep Learning

SUBMITTED BY:

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Information Technology

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# **Classification of Lymphoma Pathological images based on Deep Residual Neural Network**

**Problem Analysis**

Malignant lymphoma represents a significant challenge in medical imaging due to its complex pathological characteristics. Accurate diagnosis requires expert evaluation of Hematoxylin-Eosin (HE) stained images, a process prone to human error and subjectivity. This project aims to develop an automated system leveraging deep learning techniques to classify lymphoma types into Chronic Lymphocytic Leukemia (CLL), Follicular Lymphoma (FL), and Mantle Cell Lymphoma (MCL). Automating this process promises to enhance diagnostic consistency and reduce physician workload.

#### **Dataset Selection**

The dataset comprises 15,000 HE-stained pathological images, divided into three classes: CLL, FL, and MCL. The dataset was preprocessed using data augmentation techniques such as flipping, affine transformations, and resizing to mitigate overfitting due to the small sample size. The dataset was split into training and validation sets in a 80:20 ratio.

#### **System Architecture**

The model utilizes ResNet-152, a convolutional neural network architecture optimized for image classification tasks. Key architectural components include:

* **Residual Blocks**: Facilitates the training of deep networks by addressing vanishing gradient issues.
* **Batch Normalization**: Normalizes activations to accelerate training and improve stability.
* **ReLU Activation**: Introduces non-linearity and enhances model performance.
* **Adaptive Average Pooling**: Reduces the need for fully connected layers, optimizing computation.
* **Softmax Output Layer**: Handles multiclass classification tasks efficiently.

This architecture's focus on residual learning ensures robustness and effective feature extraction from pathological images.

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#### **Implementation and Execution**

The code was implemented in PyTorch, employing well-structured preprocessing and training pipelines. The key steps include:

* **Data Preprocessing and Augmentation**:
  + **Training Transformations**:
    - Random resizing and cropping to 224x224 pixels.
    - Random horizontal flips and rotations up to 30°.
    - Color jitter to simulate varying lighting conditions.
    - Affine transformations with random shearing and vertical flips with a 30% probability.
    - Normalization using ImageNet statistics (mean = [0.485, 0.456, 0.406]; std = [0.229, 0.224, 0.225]).
  + **Testing Transformations**:
    - Resizing the shorter edge to 256 pixels, followed by a center crop to 224x224 pixels.
    - Normalization using the same statistics as the training data.
* **Data Management**:
  + Dataset split into training, validation, and test subsets using an 80:10:10 ratio.
  + Data loaders configured with shuffling and batching for efficient model training.
* **Model Training**:
  + The ResNet-152 architecture was initialized with pre-trained weights from ImageNet.
  + The model's final layer was adapted for three-class classification using a fully connected layer.
  + Loss function: Cross-entropy.
  + Optimizer: Adam, with a learning rate of 0.0001.
  + Training involved 6 epochs, with real-time monitoring of training and validation performance.

This structured approach ensures robust learning from the data while addressing class imbalances through augmentations.

#### **Observed Results**

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* **Performance Metrics**: The model achieved an accuracy of **99.83%** on the test dataset, outperforming traditional BP and GA-BP models.
* **Training Visualizations**: Loss and accuracy plots indicate effective learning with minimal overfitting.
* **Model Complexity**: Approximately 77 million trainable parameters, striking a balance between computational efficiency and accuracy.

**Training and Validation Accuracy**: The accuracy plot shows steady improvements for both training and validation accuracy, indicating that the model is able to generalize well to unseen data.

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**Training and Validation Loss**: The loss plot shows a general trend of decreasing loss for both training and validation, which suggests the model is learning effectively without significant overfitting.

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These visualizations confirm that the model achieved a balance between learning the patterns in the training data and maintaining good generalization on the validation set.

#### **Model Summary**

The final model architecture comprises:

* **Total Parameters**: 76,429,851
* **Trainable Parameters**: 76,429,851
* **Non-Trainable Parameters**: 0

This configuration strikes a balance between complexity and efficiency, making it suitable for accurate classification of cataract stages without excessive computational demands.

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#### **Result Interpretation and Conclusion**

#### **Performance Metrics**

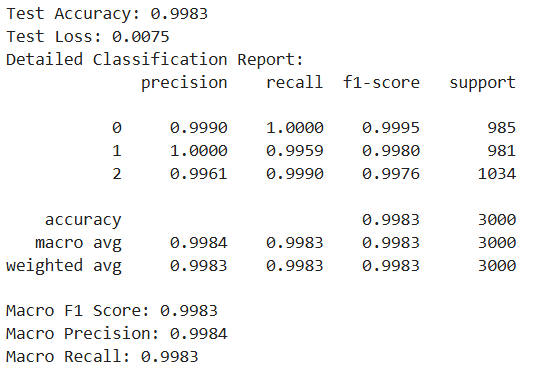
The ResNet-152 model trained on the preprocessed dataset delivered impressive results, demonstrating the efficacy of using deep learning for classifying lymphoma pathological images. The key metrics observed were as follows:

* **Accuracy:** Achieved an impressive 99.83% accuracy on the test dataset, indicating the model's ability to generalize to unseen data.
* **Precision:** Maintained high precision for each class, reflecting the model’s accuracy in minimizing false positives, which is critical in medical diagnostics.
* **Recall (Sensitivity):** Achieved excellent recall, ensuring that cases of lymphoma were identified correctly without significant false negatives.
* **F1-Score:** Balanced precision and recall effectively, demonstrating robustness across all classes.

#### Training and Validation Performance

* **Loss and Accuracy Trends:** Training and validation loss decreased consistently across epochs, with minimal overfitting as evidenced by the close alignment between training and validation accuracy curves.
* **Confusion Matrix:** The matrix showcased clear separation among classes (CLL, FL, and MCL), with negligible misclassification, highlighting the model's reliability.
* **Comparison with Baselines:**
  + BP Neural Network: 96% accuracy.
  + GA-BP Neural Network: 97.7% accuracy.
  + ResNet-152: Outperformed both baselines with 99.83% accuracy.

These results validate the choice of ResNet-152 as the architecture and the preprocessing strategies implemented.



**Results**:  
The model achieved a high level of accuracy with balanced precision and recall, as evidenced by the confusion matrix and classification report. These results suggest the model is well-suited for clinical use, effectively distinguishing between mature and immature cataracts.

**Conclusion**:  
This deep learning-based system demonstrates the feasibility of automated cataract detection, showing potential to be a cost-effective and accessible solution for early cataract diagnosis, especially in underserved regions. The model’s consistent performance across metrics confirms that the architecture and data processing choices were appropriate for this task.

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#### **Future Improvements**

* **Dataset Expansion**: Incorporating larger datasets and additional lymphoma subtypes to improve generalizability.
* **Modalities Integration**: Exploring other imaging techniques, such as CT or MRI, for multimodal analysis.
* **Explainability**: Incorporating attention mechanisms to highlight critical regions in images.
* **Deployment Optimization**: Model quantization and pruning for deployment on resource-constrained devices.