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Optimizing digital histologic colorectal cancer detection using MobileNet-based transfer learning

A diagnostic study

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ABSTRACT

Purpose: Colorectal cancer (CRC) is a major global health challenge, with an increasing incidence among younger populations. However, traditional screening methods lack comprehensiveness. The proposed work aimed to develop and evaluate a lightweight, accurate, deep learning model for classifying CRC from histo-logical images using MobileNetV3 (Google Research)-based transfer learning.

Methods: This study presents a MobileNetV3-based transfer learning model, trained and validated on two publicly available datasets: LC25000 and Kather_texture_2016. The model was fine-tuned using optimized hyperparameters and evaluated in a Python-based environment with graphics processing unit (GPU) support. The performance metrics included classification accuracy and latency.

Results: The proposed MobileNetV3-based model demonstrated high classification accuracy across all cat-egories and exhibited robust performance, even for cancer types not seen during training. The model achieved an average detection latency of approximately 0.2014 seconds per sample. These results highlight the efficiency of the model and its potential for integration into the clinical workflow.

Conclusion: The proposed MobileNetV3-based transfer learning model offers a scalable and effective solution for analyzing CRC histological images. While the performance on benchmark datasets is promising, an external test using real-world clinical data is needed to support broader clinical deployment. Future studies will focus on external testing using hospital-grade datasets and on expanding the model's capabilities to other cancer types.

Keywords: Colorectal neoplasms; Deep learning; Histopathology image; Machine learning; Medical image; MobileNetV3

INTRODUCTION

Colorectal cancer (CRC) has a high mortality rate and an increasingly rising incidence. CRC remains a significant global health concern and ranks among the top three cancers worldwide in terms of both incidence and mortality [1]. Early detection and accurate diagnosis are critical for improving survival rates, particularly because the disease increasingly affects younger populations. Histological examination of colorectal tissue biopsies is the current gold standard for CRC diagnosis; however, manual interpretation by pathologists is time-consuming, subject to inter-observer variability, and limited by human fatigue and resource constraints. With the advent of digital pathology, whole-slide imaging has enabled the digitization of histological samples at high resolution, opening the door for the integration of artificial intelligence (AI) in diagnostic workflows. Deep learning, particularly convolutional neural networks (CNNs), has shown remarkable success in various medical image classification tasks. However, training deep models from scratch on histopathological data requires large, annotated datasets and extensive computational resources, both of which are often inaccessible in clinical settings.

Transfer learning is effective in addressing this problem by allowing models trained on large image datasets to be tailored for specific tasks with fewer domain-specific data. In this study, we examined the performance of MobileNetV3 (Google Research), a lightweight and efficient CNN architecture, for the classification of CRC in digital histologic images. MobileNetV3 is particularly effective for tiered implementation in environments with limited resources due to its low computational cost without compromising effectiveness. This paper proposes an optimized transfer learning framework using MobileNetV3 variants to improve CRC detection accuracy while reducing model complexity. This study employed a publicly available histologic dataset to train and validate the model and assessed its performance with standard metrics: accuracy, precision, recall, F1 score, and area under the curve (AUC). The results indicate that MobileNetV3 achieves the desired performance outcomes when properly tuned. It has high diagnostic accuracy at lower computational costs, making it suitable for practical applications in modern digital pathology systems. This study aimed to address the growing gap in AI-assisted oncologic diagnostics by enhancing the productivity and precision of CRC detection using histological images.

This summary focuses on the applications of deep and transfer learning, particularly in MobileNet-based CRC detection, image processing, and related techniques. This demonstrates the impact of different methods and approaches over time.

Another study applied an Adaptive Moment Esimation (Adam) optimizer and transfer learning using a pre-trained MobileNet model to improve the performance and reduce overfitting for CRC classification. For the colorectal dataset, the model attained an accuracy of 97.2%. As mentioned in the study, the model's performance seems to depend on the quality of the dataset and the chosen preprocessing methods [2]. An advanced transfer learning model known as EfficientNetB3 (Google Research) was employed to enhance the detection of colon and lung cancers. This study illustrated the applicability of transfer learning techniques to pathological imaging studies. This model recorded the highest F1 score. This study underscores the need for additional testing on other datasets to determine true model generalizability [3].

Using an explainable deep learning approach combined with ShuffleNet (Megvii, Face++) to classify colon data resulted in high classification accuracy. Nevertheless, the study noted possible limitations in practice due to discrepancies in data quality and staining techniques [4]. Advanced deep AI models claim significant progress in cancer detection technology because they achieve up to 100% accuracy on a subset of histopathological images. However, the study noted that the model lacked external validation to assess its robustness across different populations [5].

CNN-based models have also been used to predict survival rates of patients diagnosed with CRC. A model built using 100,000 histological images from the renowned Darmkrebs: Chancen der Verhutung durch Screening (DACHS) and The Cancer Genome Atlas (TCGA) datasets was designed to classify the two primary regions of interest: stroma and tumors. This approach is particularly noteworthy because it directly interprets histopathological images with an accuracy of 94% [6]. The proposed DFCNet model, by Alsubai [7], which incorporates deep learning alongside metastasis information, shows promise for high accuracy in identifying lung and colon cancers, indicating that predictive precision could improve further with clinical metadata.

In another study, researchers built a model to forecast five-year survival rates for patients with CRC, from images of their tumor tissues. This study was performed on 420 patients from the Helsinki University Central Hospital using a CNN-based technique. These findings suggested that the deep learning classification network yielded a mean AUC score of 69%. Hence, deep learning methods are flexible and effective for processing images of different dimensions [7].

The standard method for diagnosing CRC has long relied on subjective histopathological assessment. In one study using a colorectal histology dataset, transfer learning was applied to adjust pre-trained CNN architectures and test various machine-learning classifiers. Among the 108 configurations tested, the combination of DenseNet169 [8] and a support vector machine architecture using the radial basis function kernel was the most effective, reaching an accuracy of 92.083% and an F1 score of 92.117%.

Another study introduced MobileNet, a cutting-edge mobile architecture that enhances performance across a range of tasks and benchmarks, while accommodating various model sizes, along with efficient techniques for object detection (SSDLite; Google Research) and semantic segmentation (Mobile DeepLab; Google Research). MobileNet employs an inverted residual structure with shortcut connections between slim bottleneck layers and lightweight depth-wise convolutions for feature filtering. This performance can be improved by eliminating nonlinear activation functions in narrow layers [9]. In another study, MobileNet was employed as an efficient model specifically designed for mobile and embedded vision tasks. To ensure lightweight architecture, the model was constructed using depth-wise separable convolutions. The authors proposed two global hyperparameters that efficiently balance latency and accuracy, allowing the model to optimize its size for application requirements [10].

In another study, three hybrid MobileNet designs were developed to prioritize accuracy while minimizing size and computational complexity, making them ideal for deployment in microcontroller units with limited resources. These models feature several key enhancements, including DropActivation (Nanjing University) instead of rectified linear units (ReLU), and random erasing regularization to combat overfitting [11]. Palmprint recognition has become increasingly popular due to its ability to handle low-resolution images, cost-effectiveness, and high accuracy [12]. Another study introduced a new network called FD-MobileNet, which was explicitly designed for minimal computational budgets ranging from 10 to 140 million floating point operations per seconds (MFLOPs). By incorporating a fast down-sampling strategy within the MobileNet framework, FD-MobileNet achieves both efficiency and accuracy [13].

The evolution of machine learning and deep learning algorithms offers significant potential for enhancing the accuracy and speed of CRC diagnosis using histological image analysis. In particular, AI can support clinicians by automating the classification of tissues obtained from colonoscopic biopsies, thus facilitating earlier and more reliable detection without disrupting current diagnostic pathways.

METHODS

The increasing prevalence of CRC in the younger population has become a concern in the medical field, highlighting the need for more sophisticated and precise screening and diagnostic methods. To address this concern, AI-based approaches—especially transfer learning techniques such as MobileNet—have the potential to automate the diagnostic workflow. As one of the most powerful deep learning techniques, transfer learning has excelled in image recognition tasks and shows promise for automated CRC detection.

This study proposes a MobileNetV3 model that classifies histological images for CRC diagnosis. Its main aim was to develop and test a compact, high-efficiency transfer learning model suitable for supporting histological decision-making. This system was proposed as an adjunct to existing diagnostic processes to improve classification accuracy, reduce diagnostic turnaround times, and broaden access to advanced diagnostics. This model can improve clinical decision-making by reducing diagnostic workloads and accelerating the classification processes.

The proposed system architecture is shown in Fig. 1, which presents a high-level design overview of the model schematic. It begins with the data sources. The acquisition segment of the model involved collecting histological images and storing them in centralized repositories. LC25000 (University of Göttingen) [14] and Kather_texture_2016 (Mannheim University Medical Center) [15] are publicly available datasets; the former contains 25,000 labeled histological images and the latter contains 5,000. Consequently, these datasets were stored in a centralized data storage system for processing. Preprocessing involved conversion to grayscale, image resizing to uniform dimensions, and normalization. The processed datasets were then routed to the model-training pipeline, where feature extraction pertinent to CRC was performed by fine-tuning the MobileNetV3 architecture pre-trained on ImageNet (Stanford University).

Fig. 2 presents a detailed dataflow diagram illustrating the training and testing phases. The data were pre-processed and split into training (80%) and testing (20%) subsets. Training continued iteratively until the learning criteria were met, after which the model was validated using unseen testing data. This flow supports future data imports from cloud environments and facilitates consistent model updates and clinical

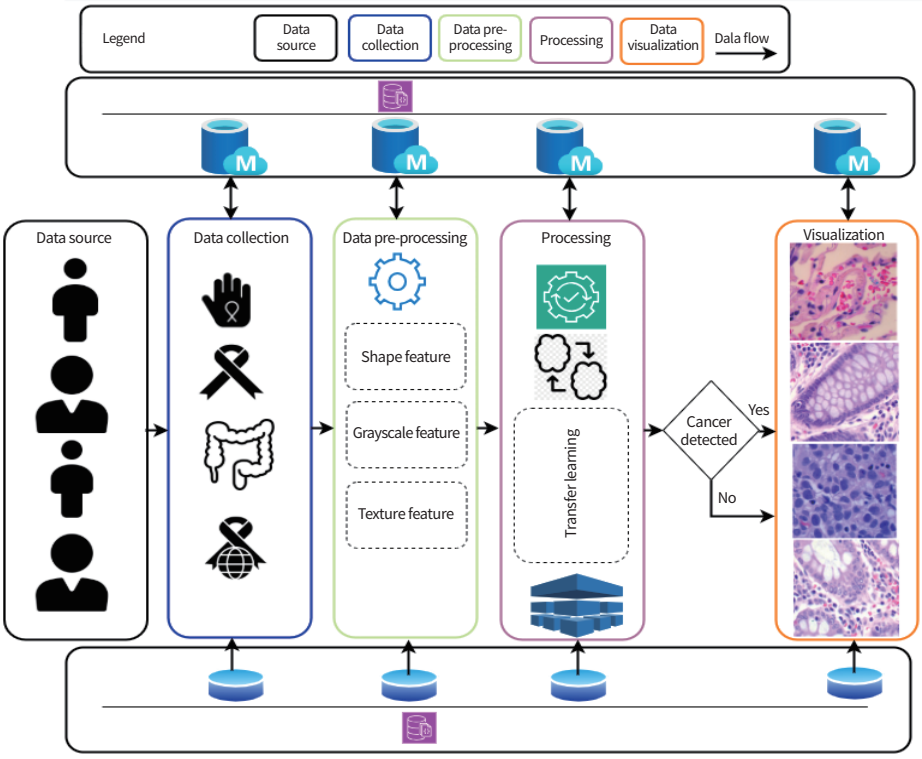

Fig. 1. **Proposed methodology of colorectal cancer detection using MobileNetV3.**

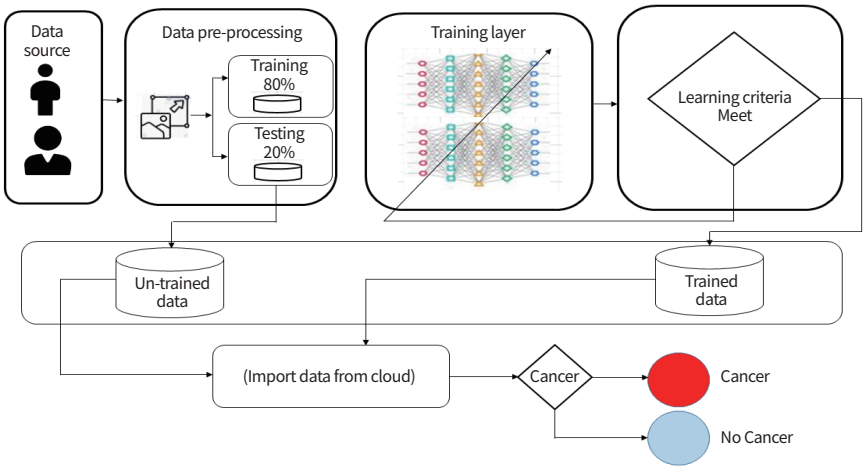

Fig. 2. **Data flow diagram for the proposed model.**

deployment.

To balance computational efficiency with domain-specific learning, the early feature extraction layers were frozen, preserving pre-trained ImageNet representations, whereas the final convolutional and classification layers were fine-tuned on the histopathological CRC images. The network architecture was enhanced by appending a global average pooling layer, followed by a dropout layer (rate = 0.5) to reduce overfitting, and a softmax output layer configured for the number of classes in each dataset (five for LC25000 and eight for Kather_texture_2016). Training was conducted with a learning rate of 0.001, a batch size of 64, and 260 epochs using a random search strategy. The model was compiled using the Adam optimizer and categorical cross-entropy as the loss function. Early stopping was performed to prevent overfitting. The final model contained 67,077 trainable parameters. After training, the model was evaluated using unseen testing data. If CRC-related abnormalities are detected, the model generates ac-

Table 1. Pseudocode of proposed colorectal cancer detection model

Serial no.	Steps
1	Start
2	Import required libraries
3	Data loading:
	1. For each folder in the data directory:
	i. Read all image files
	iii. Assign labels based on folder names
4	Perform feature extraction
5	Model-training phase
5.1	Initialization of the training process
5.2	Implement the MobileNet model and configure classification layers
5.3	For each training pattern
	1. Perform the feedforward phase to
	i. Calculate activations for each hidden layer
	2. Compute output error signals and hidden layer error signals
	3. Update the weights of the output layer
5.4	Increment the iteration count
5.5	Check detection criteria: if no criteria are satisfied, return to step 4
	Else, go to step 5.6
5.6	Store in the cloud
6	Testing phase
6.1	Retrieve trained data from the Cloud.
6.2	Import input data for the test
6.3	Predict cancer classification using the trained model
6.4	If cancer detected → Store the result
6.5	Else → Store as non-cancerous
7	End

tionable outputs, which are visualized via clinical dashboards and stored securely in the cloud for future reference.

The MobileNetV3-based transfer learning model integrates a convolutional base for extracting spatial features. Table 1 outlines the step-by-step procedural logic, including data import, feature extraction, propagation, and testing. All stages were designed to be modular and reproducible to support future model upgrades and clinical deployment.

The proposed MobileNetV3-based model can serve as an effective AI-assisted diagnostic tool for CRC detection by providing a transparent, scalable, and accurate classification framework. The cloud infrastructure ensures the secure storage, version control, and accessibility of the processed results, reinforcing the system's utility for real-time and retrospective clinical evaluation.

Institutional Review Board approval was waived due to the retrospective nature of the data and informed consent was waived due to the anonymous nature of the data.

RESULTS

Image-level classification is essential for generating accurate predictions for each histological sample. In this study, MobileNetV3 convolutional layers were adapted to increase the receptive field and capture high-level structural features within the histologic images. The provided dataset is a well-known benchmark in CRC research, as it offers both labeled and unlabeled training data. It is essential to mention that test data includes cancer types not present in the training set, enabling a better evaluation of the model's generalization ability, which is crucial for assessing the predictive performance of the model. Model input was pre-processed to address the inconsistencies related to the validity and integrity of the data before deployment. Monitoring the activation and propagation of hidden neurons, as well as network behavior, confirmed that learning occurred at different stages of the network with respect to domain-specific features. All experiments and simulations were conducted within the Python environment. The operating system (OS) used was 64-bit Windows 10, with an Intel Core processor, graphics processing unit (GPU) support, and 32 GB of random-access memory (RAM). The proposed system has a sample detection latency of approximately 0.2014 seconds and renders classification decisions within milliseconds for real-time analysis. As stated in Equations (1) to (9), the output from the system is derived from statistical measures that reveal its comparative effectiveness against existing CRC models.

Considering CRC diagnostics and serving as an adjunct tool for medical practitioners, the proposed MobileNetV3-based model aims to enhance histological CRC diagnostics through an accurate, transparent, and scalable classification pipeline.

$$\text{Sensitivity} = \text{true positive rate (TPR)} = \frac{\sum TP}{\sum TP + FN} \quad (1)$$

$$\text{Specificity} = \text{true negative rate (TNR)} = \frac{\sum TN}{\sum TN + FP} \quad (2)$$

$$\text{Detection accuracy} = \frac{\sum TP + \sum TN}{\sum P + N} \quad (3)$$

$$\text{Miss classification rate} = \text{1-detection accuracy} \quad (4)$$

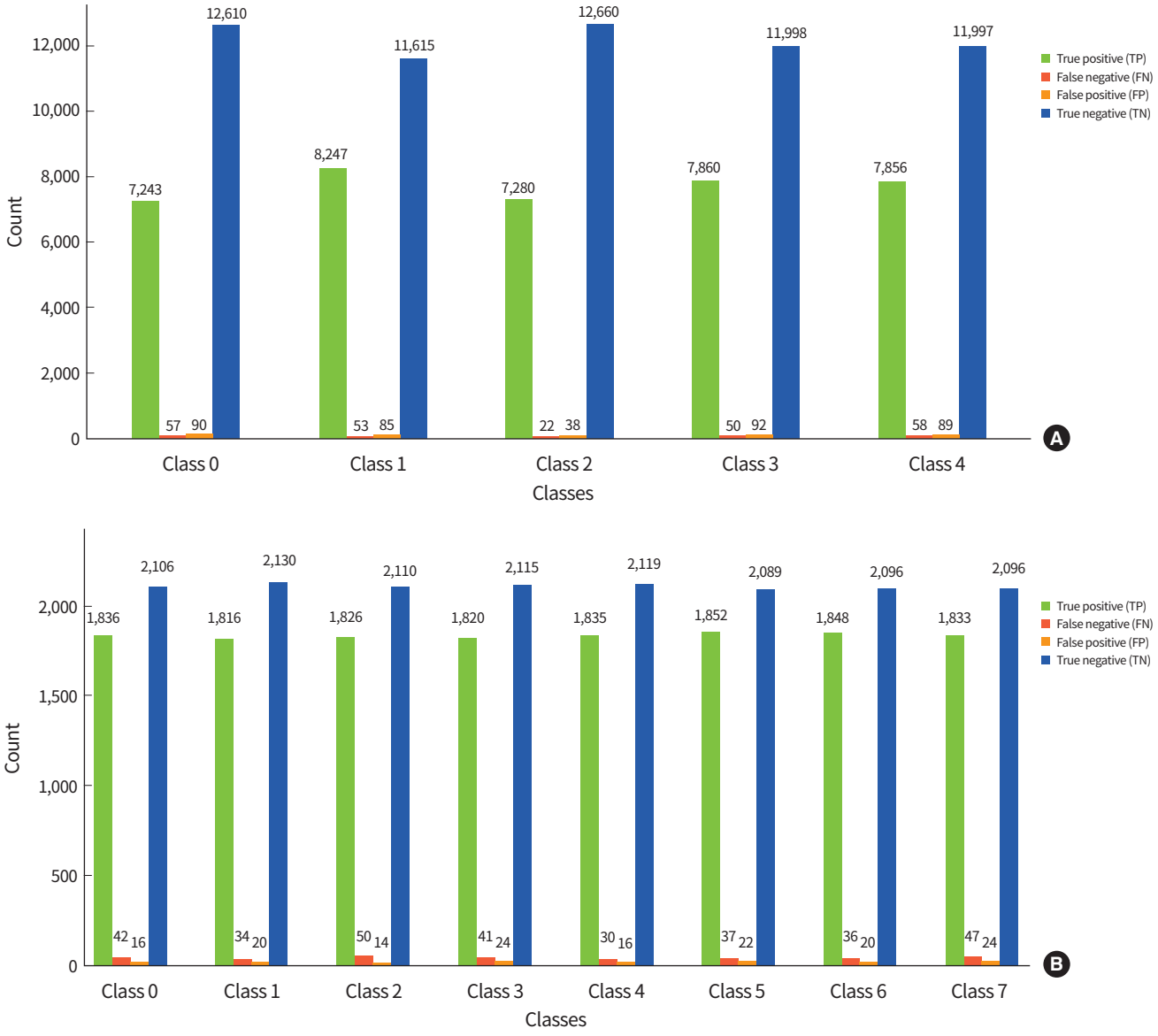

Fig. 3. (A) Metrics of the training phase in the proposed model of the LC25000 dataset. (B) Metrics of the training phase in the proposed model of the Kather_texture_2016 dataset.

$$\text{Fallout} = \text{false positive rate (FPR)} = \frac{\sum FP}{\sum FP + TN} \quad (5)$$

$$\text{Likelihood positive ratio (LR+)} = \frac{\sum TPR}{\sum FPR} \quad (6)$$

$$\text{Likelihood negative ratio (LR-)} = \frac{\sum FPR}{\sum TPR} \quad (7)$$

$$\text{Positive preditive values (PPV)} = \frac{\sum TP}{\sum \text{TP} + FP} \quad (8)$$

$$\text{Negative predictive value (NPV)} = \frac{\sum TN}{\sum \text{TN} + FN} \quad (9)$$

Fig. 3A shows how the class labels in the LC25000 dataset in the training phase are subdivided into true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). This offers a synopsis of the classification results. This multiclass subdivision demonstrates the model's capability to accurately detect features of CRC across various levels of the diagnostic class spectrum. In all the classes (class 0 to class 4), it is observable that the true negative (TN) counts for all the classes are also measured above a significance threshold between 11,615 and 12,660. This means that the model performs appropriately in terms of specificity, as reflected by the high number of TN, which represent the majority of non-rele-

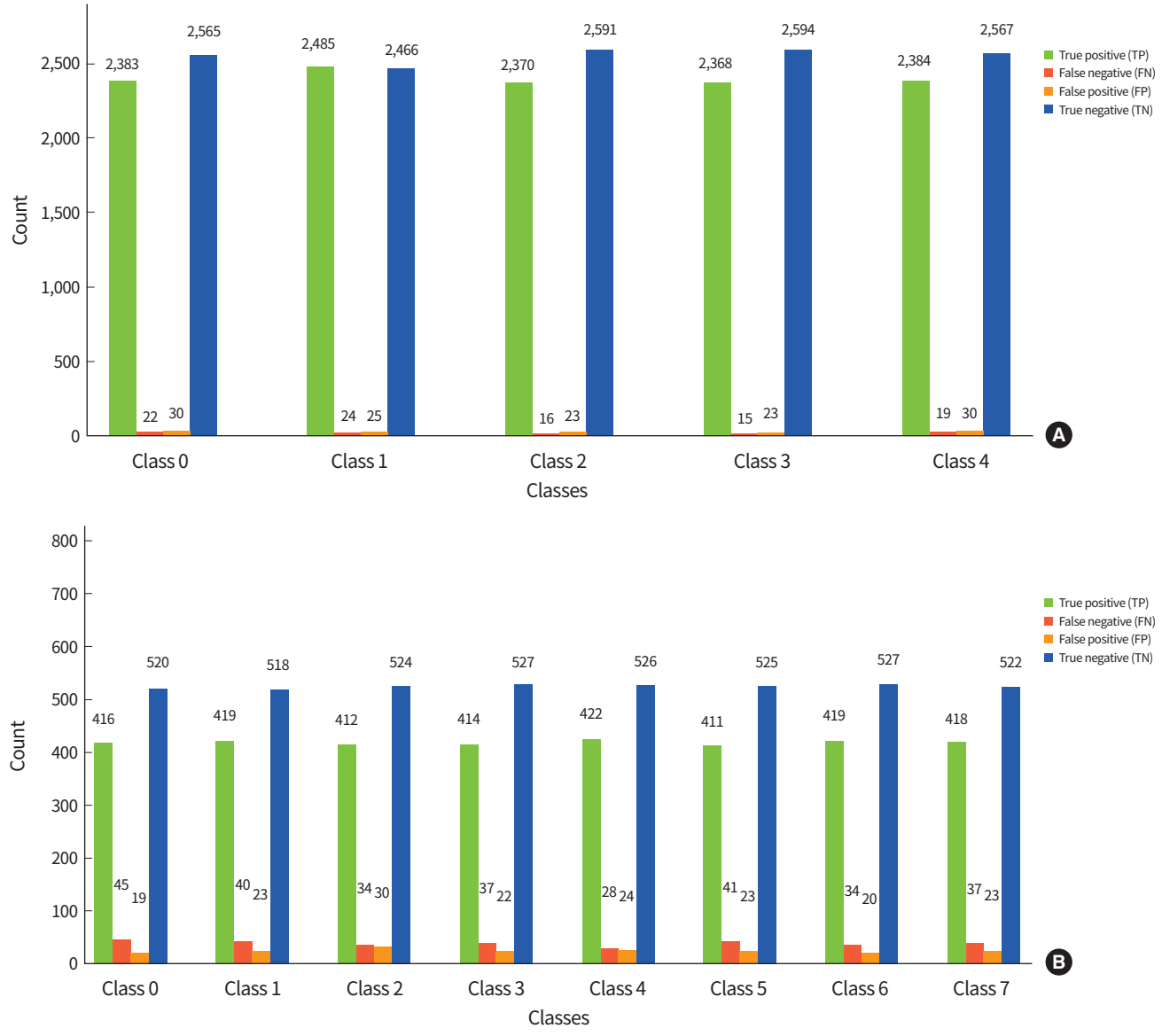

Fig. 4. (A) Metrics of the test phase in the proposed model of the LC25000 dataset. (B) Metrics of the test phase in the proposed model of the Kather_texture_2016 dataset.

vant instances that are not pertinent to that class. Likewise, the TP values are equally high: class 3 has a value of 7,860, while class 1 has 8,247, enabling the model to adequately interpret emerging target values.

Fig. 3B illustrates the classification results across the eight classes of the Kather_texture_2016 dataset in the training phase. The model consistently showed high TP and TN counts for each class, indicating strong diagnostic capability. TP values were uniformly high (ranging from 1,816 to 1,852), whereas TN values remained high (between 2,089 and 2,130), reflecting the model's reliability in identifying both positive and negative cases. However, FN and FP, although relatively low, were present in all classes. For instance, class 2 exhibited 50 FN cases—the highest among all—suggesting slightly reduced sensitivity for that class. Similarly, modest FP values (ranging from 14 to 42) suggest occasional misclassifications that affect precision.

Fig. 4A shows the classification performance for the five classes using the proposed MobileNetV3-based model of the LC25000 dataset in the testing phase. The model demonstrated consistently high TP and TN counts across all classes, with TP values ranging from 2,368 to 2,485 and TN values ranging from 2,466 to 2,594. This indicates strong model performance in correctly identifying both positive and negative cases.

Table 2. Performance evaluation of the proposed model with different statistical measures

	Class	Detection accuracy (%)	TPR (%)	TNR (%)	Misclassification rate (%)	FPR (%)	LR+	LR–	PPV (%)	NPV (%)
Training statistics of the LC25000 dataset	Overall	99.36	99.3	99.3	0.64	0. 6	174.8	0.006	98.9	99.6
Training statistics of the Kather_texture_2016 dataset	Overall	98.52	97.8	99.0	1.47	0.8	110.6	0.008	98.9	98.1
Test statistics of the LC25000 dataset	Overall	99.09	99.1	99.1	0.91	0.9	99.33	0.009	98.8	99.2
Test statistics of the Kather_texture_2016 dataset	Overall	94.00	91.7	95.7	6.00	4.16	22.16	0.045	94.7	93.3

TPR, true positive rate; TNR, true negative rate; FPR, false positive rate; LR, likelihood ratio; PPV, positive predictive value; NPV, negative predictive value.

Table 3. P-values and confidence scores of MobileNetV3 vs. ShuffleNet on LC25000 and Kather_texture_2016 datasets for recall, precision, DSC, and IoU

Dataset	Models	Evaluation	Recall	Precision	DSC	IoU
LC25000	MobileNetV3 and ShuffleNets	P-value	0.0061	0.0034	0.0016	0.0017
		Confidence score	99.21%	98.92%	99.06%	98.14%
Kather_texture_2016	MobileNetV3 and ShuffleNet	P-value	0.0121	0.0352	0.0107	0.0562
		Confidence score	91.85%	94.77%	93.28%	89.41%

DSC, dice similarity coefficient; IoU, intersection over union.

Fig. 4B shows the classification metrics for the eight classes, demonstrating the performance of the proposed MobileNetV3-based model for the Kather_texture_2016 dataset in the test phase. TP and TN were consistently high across all classes, indicating the model's solid capability to identify both CRC-positive and CRC-negative instances. The TP values ranged from 411 to 422, whereas the TN values ranged from 518 to 527.

Table 2 shows that the proposed MobileNetV3-based model demonstrates strong performance on both the training and test subsets of the LC25000 dataset and the Kather_texture_2016 Dataset. During training, the overall detection accuracy reached 99.36%, with a true positive rate (TPR) and true negative rate (TNR) of 99.3% each. The model also achieved very high performance on the Kather_texture_2016 dataset, though slightly lower than the LC25000. During training, the model attained an overall detection accuracy of 98.52%, with TPR 97.8% and TNR 99.0%. Performance across all eight classes remained consistent, with positive predictive value and negative predictive value mostly above 98.5%. The low false positive rate (FPR) (approximately 0.8%) and high positive likelihood ratio (LR+) values (>100 in some classes) further indicate high classification confidence.

During testing, the model maintained robust generalization, achieving an overall accuracy of 99.09%, with the TPR and TNR values remaining at approximately 99.1%. The class-wise detection accuracy remained consistently above 98.9%, and both the misclassification and FPRs were low (<1.1%). These results confirm the model's strong generalization abili-

Table 4. Comparative results between the proposed model and existing approaches

Reference	Algorithm	Detection accuracy (%)
[16]	Random forest algorithm	84.0
[17]	Convolutional neural network	94.0
[18]	Ensemble classifier	91.67
[19]	Random forest	95.16
[20]	Z-FS-KM-MHS	94.36
[21]	K-nearest neighbors	94.0
[22]	Self-paced transfer MobileNet	96.0
[23]	Mask-RCNN	97.83
[24]	Decision tree	97.81
[25]	DNNBoT	97.2
[26]	Ensemble learning	99.30
[27]	EfficientNet-B0	98.6
[28]	Hybrid U-Net	98.1
[29]	CNN	88.26
Proposed model	MobileNetV3	99.09
	MobileNetV3	94.00

CNN, convolutional neural network.

ty and low risk of overfitting on the LC25000 dataset. Similarly, for the Kather_texture_2016 dataset, the model achieved an overall detection accuracy of 94.00%, with TPR 91.7%, TNR 95.7%, and a misclassification rate 6.00%. Although slightly lower than the training, the model maintained a high predictive reliability across all classes. Further details are available in the Supplementary Tables 1-3 and Supplementary Figs. 1-3.

Table 3 shows statistical comparison between MobileNetV3 and ShuffleNet models on the LC25000 and Kather_texture_2016 datasets. The table presents P-values indicating the statistical significance of differences in recall, precision, dice similarity coefficient, and intersection over union, along with the confidence scores.

Table 4 presents the comparative performance analysis of the proposed CRC detection model using various machine-learning techniques and previous approaches [16-29]. The accuracy and miss rate metrics were calculated for the training and test phases. These results indicate a significant improvement in accuracy, ranging from 1% to 23%, compared with existing machine-learning techniques. Thus, the proposed model outperforms existing methods for detecting CRC.

DISCUSSION

This paper presents a MobileNetV3-based transfer learning framework designed for the classification of histological images in CRC detection. Through extensive training and testing on public CRC datasets, the model demonstrated high accuracy, low latency, and robust generalizability—particularly in identifying cancer types not included in the training set. By combining computational efficiency with diagnostic precision, the proposed system is ideally suited for integration into real-time clinical workflows. Future directions include external testing using hospital-grade datasets and expanding the model to incorporate other cancer types and multimodal clinical data, thereby closing the gap between AI research and medical applications.

This study introduces a lightweight MobileNetV3 architecture that is computationally efficient and well suited for real-time diagnostic applications. Although the proposed model performed well on the CRC datasets, its performance may be influenced by the quality and quantity of the training data. In addition, the model was trained and validated solely on publicly available datasets that lack hospital-acquired, real-world clinical data, potentially limiting its generalizability to practical medical settings.

CONFLICTS OF INTEREST

No potential conflict of interest relevant to this article was reported.

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AUTHOR CONTRIBUTIONS

Conception or design: MA, MAK.
Acquisition, analysis, or interpretation of data: MA, RAN, SH, MAK, SA, SWL.
Drafting the work or revising: MA, RAN, SH, MAK.
Final approval of the manuscript: MA, RAN, SH, MAK, SA, SWL.

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