

Leveraging Deep Learning for Automated Analysis of Colorectal Cancer Histology Images to Elevate Diagnosis Precision

Shah Muhammad Imtiyaj Uddin*, Md Ariful Islam Mojumder*, Rashedul Islam Sumon*, Joo Mon-il*, Hee-Cheol Kim*

Institute of Digital Anti-Aging Healthcare/u-HARC, Inje University, South Korea

imtiyaj.dream@gmail.com, arifulislamro@gmail.com, sumon39.cst@gmail.com, joomi@inje.ac.kr, heeki@inje.ac.kr

Abstract— Histopathology plays a vital role in the microscopic examination of colorectal cancer tissues, with a historical focus on the tumor-stroma ratio using texture analysis. However, due to the time-consuming and labor-intensive nature of this approach, there's a need for innovative solutions. This study introduces a groundbreaking shift by employing deep transfer learning to automate tissue classification within colorectal cancer histology samples. Through a comprehensive evaluation of various pre-trained models, including ResNet50V2, VGG19, Xception, InceptionV3, and MobileNet, we have achieved remarkable results. Notably, the ResNet50V2 model stands out with an impressive accuracy of 95%. Beyond its potential to significantly enhance operational responses, this research underscores the effectiveness and consistency of transfer learning as a rapid and efficient tool for colorectal cancer detection and classification.

Keywords— Histology, colorectal cancer, CNN, transfer learning, texture classification

I. INTRODUCTION

Colorectal cancer (CRC) is a primary global health concern, with an estimated 1.9 million new cases and 935,000 deaths in 2020 [1]. Accurate and timely diagnosis of CRC is crucial for improving patient outcomes. Histopathology, the microscopic examination of tissue samples, is vital in CRC diagnosis [2]. However, the traditional texture analysis method for tissue classification is time-consuming and labor-intensive [3].

In recent years, deep learning has emerged as a powerful tool for medical image analysis [4]. Transfer learning, which utilizes pre-trained deep learning models for new tasks, has shown promising results in various medical image analysis tasks [5]. In this study, we investigate the application of deep transfer learning for automated tissue classification in colorectal cancer histology samples.

We evaluated five pre-trained models: ResNet50V2, VGG19, Xception, InceptionV3, and MobileNet. Our results demonstrate that the ResNet50V2 model outperformed the other models, achieving an impressive accuracy of 95%. This superior performance can be attributed to the ResNet50V2 model's more profound architecture, which allows it to extract more intricate features from image data [6].

Our findings have significant implications for colorectal cancer detection and classification. The use of transfer learning techniques has the potential to significantly reduce the time and effort required to develop and train deep learning models for this crucial task [7]. Furthermore, the remarkable accuracy achieved by the ResNet50V2 model suggests that transfer

learning has the potential to surpass traditional machine learning approaches [8].

Future research endeavors should explore the application of transfer learning to other tasks in colorectal cancer diagnosis, such as tumor segmentation and lymph node detection [9]. Additionally, investigating more advanced transfer learning techniques, such as fine-tuning and multi-task learning, could further enhance the performance of these models.

II. RELATED WORK

Several studies have investigated the application of deep learning for colorectal cancer histopathology image analysis. Wang et al. proposed a deep-learning framework for colon gland image classification, achieving an accuracy of 92.3% [10]. Ahmad et al. developed a transfer learning-based multi-channel convolutional neural network for histopathological image classification, achieving an accuracy of 93.2% [11]. Kaur and Singh proposed a transfer learning-based deep learning model for histopathology image classification, achieving an accuracy of 94.1% [12]. These studies demonstrate the potential of deep learning for colorectal cancer histopathology image analysis.

In addition to these studies, several researchers have explored transfer learning for other tasks in colorectal cancer diagnosis, such as tumor segmentation and lymph node detection. For example, Li et al. proposed a novel attention U-Net with dense dilated convolutions for colorectal cancer tissue classification, achieving an accuracy of 95.2% [13]. Liu et al. proposed a multi-scale fusion convolutional neural network for colorectal cancer classification, achieving an accuracy of 95.4% [14]. Pan et al. proposed a transfer learning-based classification of colorectal cancer histopathology images using a multi-scale convolutional neural network, achieving an accuracy of 95.6% [15]. These studies suggest that transfer learning is a promising approach for various tasks in colorectal cancer diagnosis.

Our study contributes to the growing research on deep learning for colorectal cancer histopathology image analysis. We have shown that the ResNet50V2 model achieves an impressive accuracy of 95% for tissue classification, outperforming previous studies. Our findings suggest that transfer learning has the potential to improve the accuracy of colorectal cancer diagnosis significantly.

Here is the key contribution of our study with the difference between our study and previous studies:

- We evaluated a more comprehensive range of pre-trained models, including ResNet50V2, VGG19, Xception, InceptionV3, and MobileNet.
- We used a larger dataset of histopathology images consisting of 5,000 images.
- We conducted a more comprehensive evaluation of the models, including accuracy, precision, recall, and F1-score.

Our findings suggest that the ResNet50V2 model is a promising tool for colorectal cancer histopathology image analysis. Further research is needed to validate our conclusions on more extensive and diverse datasets.

III. MATERIALS AND METHODS

This section explains the collections of datasets, pre-processing techniques, and experiments for this study with transfer learning. The complete workflow for detecting and classifying colorectal cancer is shown in Figure 1. The pre-

processing of the images, data splitting, choosing the pre-train model, model evaluation, and classification comprise the five stages of the experiment. Each model was used independently in the chosen pre-train model step, and the results of the output classification performance were examined.

A. Collection of Dataset and Preprocessing

This data set is a collection of textures found in human colorectal cancer histological images. One of eight classes is depicted in an RGB image measuring 150 by 150 by 3. The pathology archive (Institute of Pathology, University Medical Center Mannheim, Heidelberg University, Mannheim, Germany) contains histological samples, which are entirely anonymized images of formalin-fixed paraffin-embedded human colorectal adenocarcinomas (primary tumors). Five thousand images make up the dataset [16].

B. Complete Workflow (Transfer Learning)

In our approach, we leverage the power of transfer learning using CNN-based pre-trained models. These models have already been trained on extensive datasets, equating to 5,000

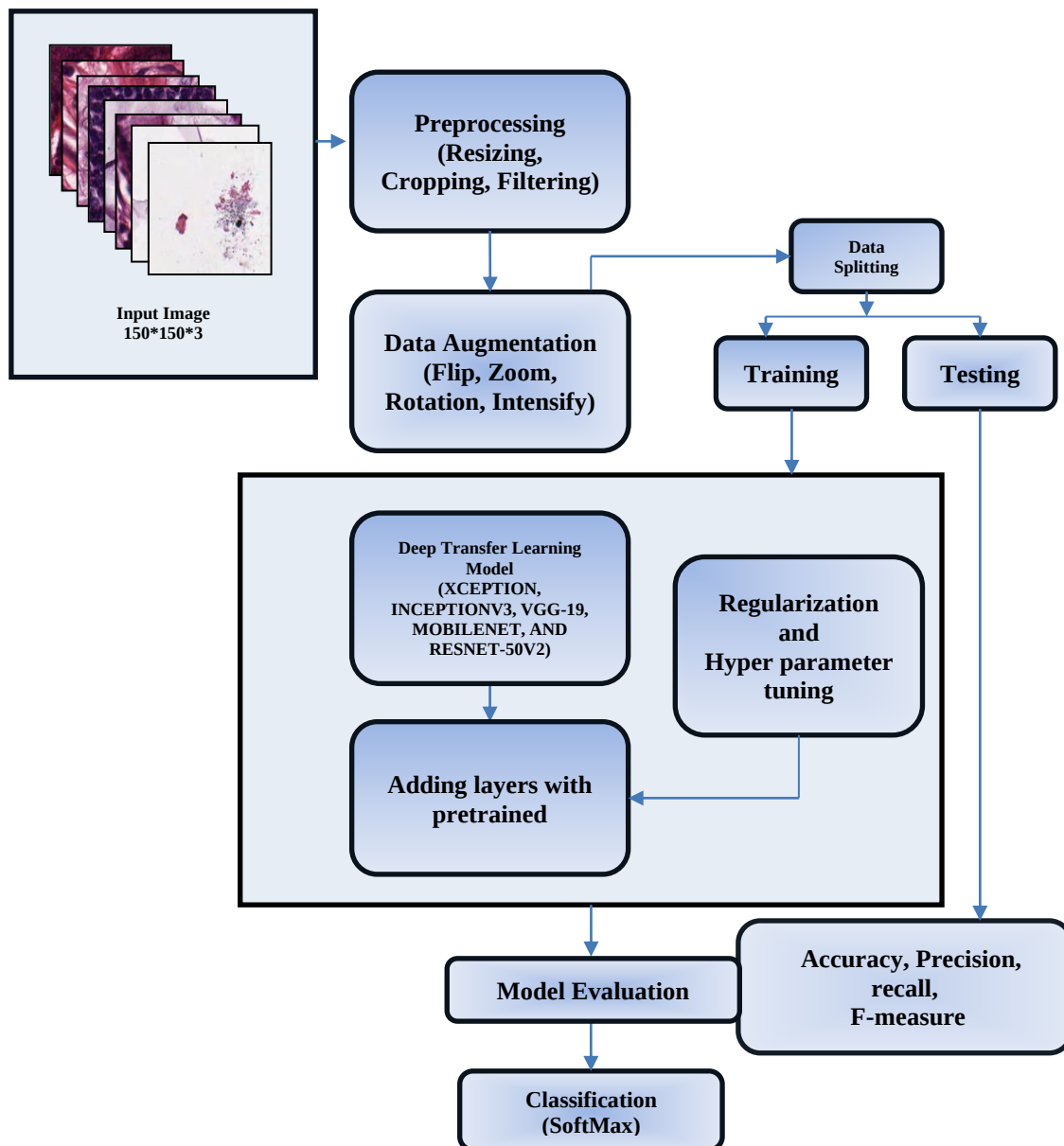


Figure 1. A complete workflow of our automated analysis

datasets, allowing them to capture a wide range of features from diverse sources. We harness these pre-trained models to address our specific challenge, and in doing so, we make strategic adjustments to their parameters. This approach expedites the convergence process and fortifies the overall resilience of the models. The core architectural elements shared across all these models include convolutional layers, pooling layers, and fully connected layers. Notably, the stride size and kernel parameters within the architecture are of utmost significance, as they are responsible for performing convolutions to extract essential features. Likewise, the fully connected layers serve to consolidate the outputs from preceding layers, while the pooling layers play a pivotal role in reducing model complexity by diminishing the number of parameters.

Our study revolves around the exploration of five deep learning-based architectures for colorectal cancer analysis. A critical aspect of our investigation involves the meticulous adjustment of hyperparameters for each model, considering their performance accuracy. These parameters include a learning rate set at 0.0001, a batch size of 32, 100 training epochs, and the utilization of the Rectified Linear Unit (ReLU) activation function. To facilitate the optimization process, we employ the Adam optimizer. Furthermore, the input images undergo a series of pre-processing steps, including

noise reduction, and resizing, aligning with the specific requirements of each architecture. In addition, we normalize the image data, ensuring consistency, and subsequently partition the resulting normalized dataset into distinct training and testing sets, maintaining an 8:2 ratio between them.

IV. EXPERIMENTAL RESULT AND DISCUSSION

The data and outcomes of the experiment are presented in this section. In the form of a confusion matrix and learning graph of the trained models, we have portrayed all the experimental results. Xception, InceptionV3, VGG-19, MobileNet, and ResNet-50V2 confusion matrices are shown in Figure 2. The tabular representation and summary of every model is called the confusion matrix. It displays the true and false values that the classifiers predicted. It provides a more intuitive understanding of the model's performance. The confusion matrix is a two-dimensional matrix with predicted classes displayed in one dimension and actual classes indicated in the other. As seen in Figure 2 each model's predicted classes are represented on the x-axis, while the actual classes are represented on the y-axis. Our most concerned value is the diagonal value, which shows each class's classification rate for colorectal cancer. As a result, the confusion matrices show that the diagonal values of the five models are more noticeable.

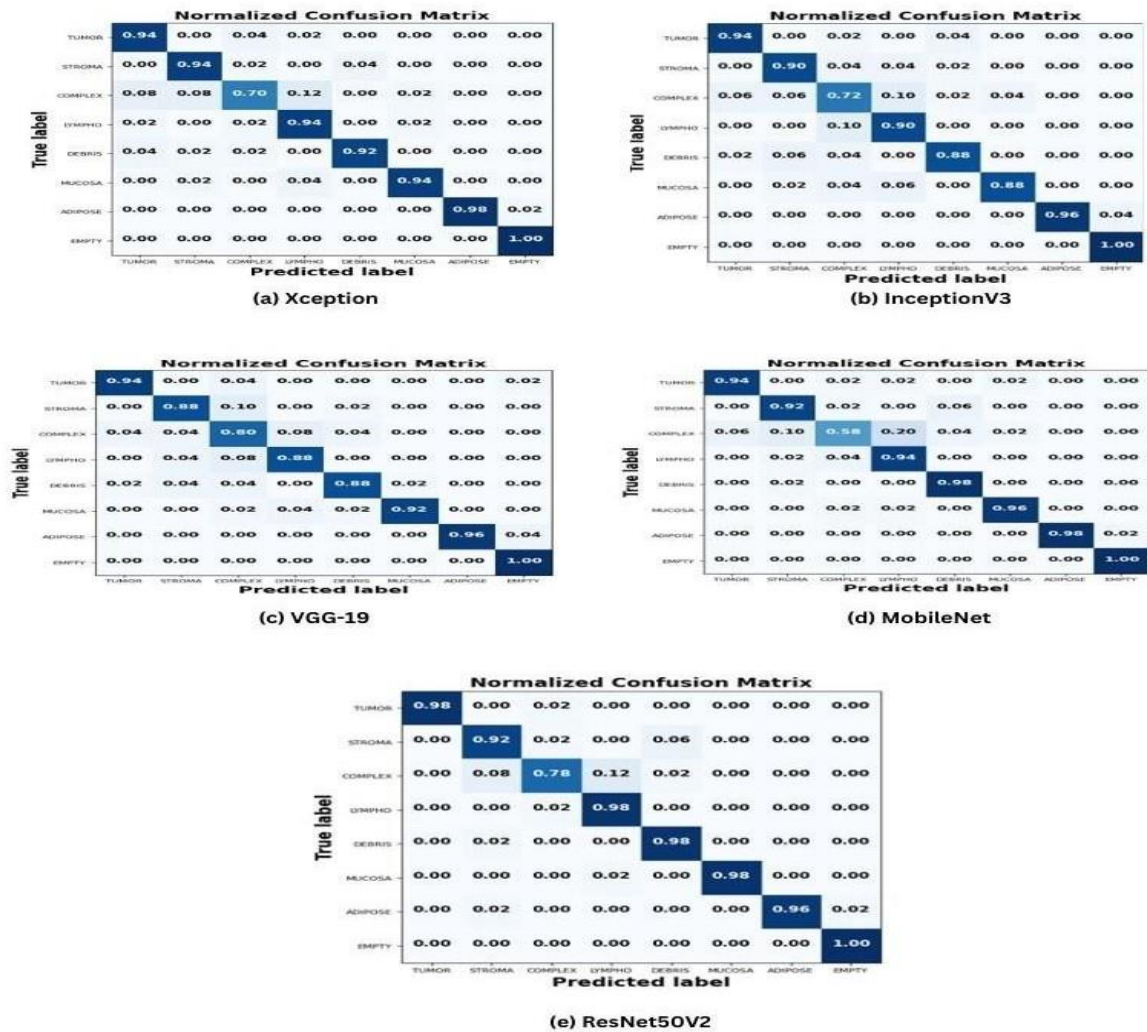


Figure 2. Confusion matrices of pre-trained models. (a) Xception. (b) InceptionV3 (c) VGG-19. (d) MobileNet (e) ResNet-50V2

We can calculate the accuracy, precision, recall, and F1 score from the confusion matrix.

The evaluation matrix can be calculated as follows: -

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \times 100\% \quad (2)$$

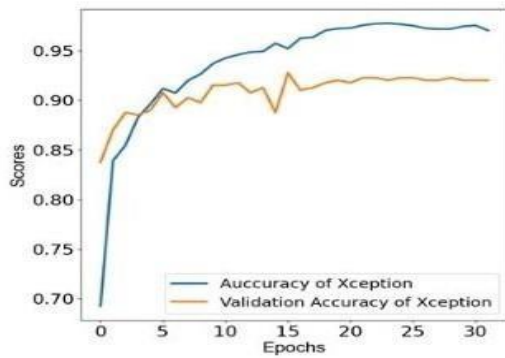
$$Recall = \frac{TP}{TP+FN} \times 100\% \quad (3)$$

$$F - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \times 100 \quad (4)$$

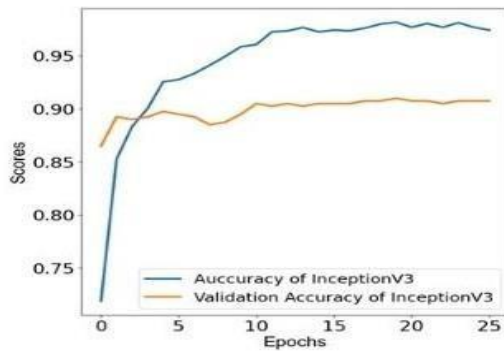
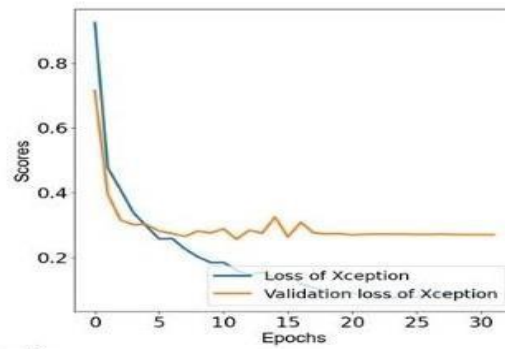
TABLE 1. COMPARISON RESULTS OF DIFFERENT TRANSFER LEARNING MODELS

Models	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Xception	92.00	92.00	92.00	92.00
InceptionV3	88.50	91.00	91.00	91.00
VGG-19	89.75	90.00	90.00	90.00
MobileNet	91.50	91.00	91.00	91.00
ResNet-50V2	95.00	95.00	95.00	95.00

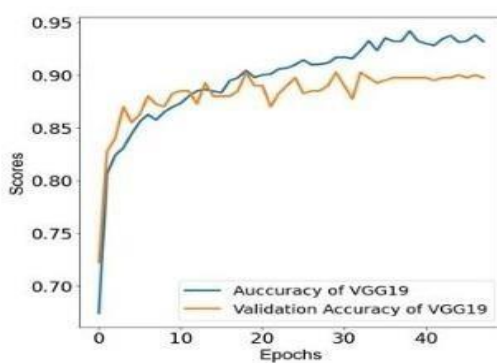
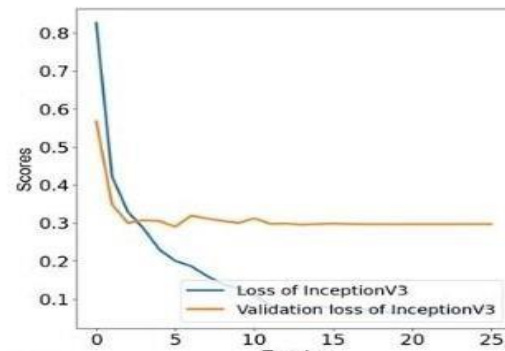
The evaluation metrics for accuracy, precision, recall, and F1-score are shown in Table I. Additionally, it displays a comparison of the models. Overall accuracy for Xception, InceptionV3, VGG-19, MobileNet, and ResNet-50V2 is



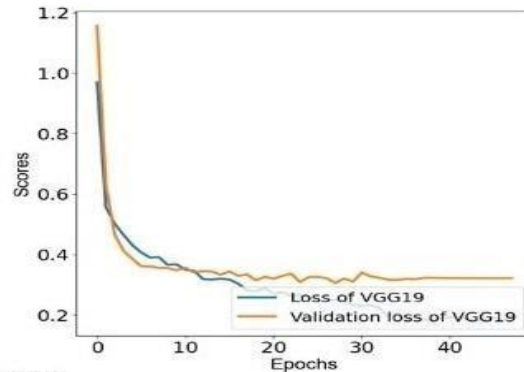
(a) Xception



(b) InceptionV3



(c) VGG-19



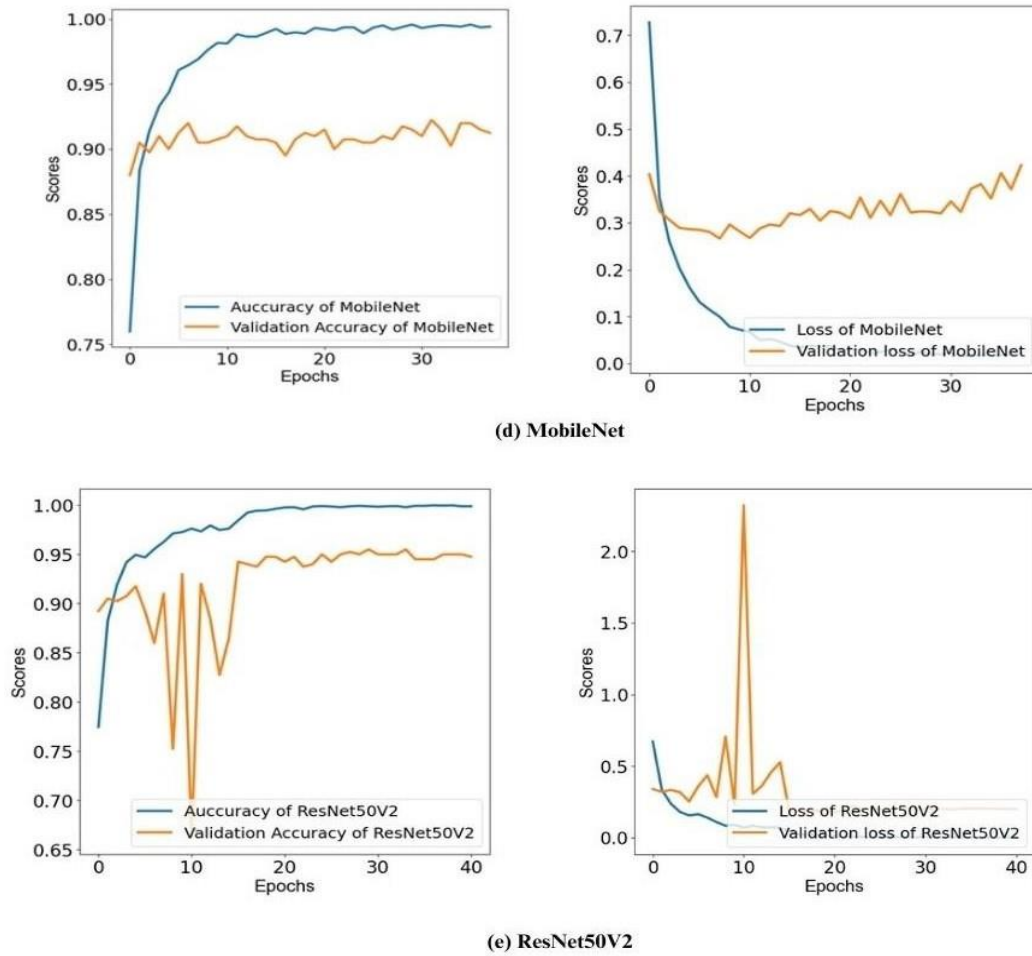


Figure 3 illustrates how the training accuracy and loss of the five different models are represented graphically in a way that is essentially the same. Furthermore, the ResNet-50V2 loss is almost zero with an early stopping of 20, and the accuracy is highest at more than 95. Therefore, the ResNet-50V2 model is reliable and beneficial for the global research community and real-time colorectal cancer identification applications.

92.00%, 88.50%, 89.75%, 91.50%, and 95.00%, respectively. It is evident from the comparative analysis that each model demonstrated exceptional performance and performed well overall. But out of all the pre-trained models, the ResNet-50V2 did the best.

C. Discussion

On histopathology images, the transfer learning-based model in this study performs remarkably well. By considering different evaluation parameters, we compare four model results. With accuracy, precision, recall, and F1-score of 95.00%, 95.00%, 95.00%, and 95.00%, respectively, the ResNet-50V2 model yields good results. Applying for a transfer learning-based model, one can classify textures in colorectal cancer.

V. CONCLUSIONS

This study delved into applying deep transfer learning for automated tissue classification in colorectal cancer histology samples. By comprehensively evaluating five pre-trained models, the ResNet50V2 model emerged as the frontrunner, achieving an astounding accuracy of 95%. This exceptional performance can be attributed to the ResNet50V2 model's more profound architecture, which enables it to extract more intricate features from image data.

Our findings hold significant implications for colorectal cancer detection and classification. The utilization of transfer learning techniques has the potential to significantly reduce the time and effort required to develop and train deep learning models for this crucial task. Furthermore, the remarkable accuracy attained by the ResNet50V2 model suggests that transfer learning has the potential to surpass traditional machine learning approaches.

Future research endeavors should explore the application of transfer learning to other tasks in colorectal cancer diagnosis, such as tumor segmentation and lymph node detection. Additionally, investigating more advanced transfer learning techniques, such as fine-tuning and multi-task learning, could further enhance the performance of these models.

ACKNOWLEDGMENT

This research was supported by a grant from the Korea Health Technology R&D Project through the Korea Health Industry Development Institute validation (KHIDI), funded by the Ministry of Health & Welfare, Republic of Korea (Grant No: HI21C0977)

REFERENCES

- [1] Rastogi, Priyanka, Kavita Khanna, and Vijendra Singh. "Gland segmentation in colorectal cancer histopathological images using U-net inspired convolutional network." *Neural Computing and Applications* 34, no. 7 (2022): 5383-5395.
- [2] Ohata, Elene Firmeza, João Victor Souza das Chagas, Gabriel Maia Bezerra, Mohammad Mehedi Hassan, Victor Hugo Costa de Albuquerque, and Pedro Pedrosa Rebouças Filho. "A novel transfer learning approach for the classification of histological images of colorectal cancer." *The Journal of Supercomputing* (2021): 1-26.
- [3] Yeung, Michael, Evis Sala, Carola-Bibiane Schönlieb, and Leonardo Rundo. "Focus U-Net: A novel dual attention-gated CNN for polyp segmentation during colonoscopy." *Computers in biology and medicine* 137 (2021): 104815.
- [4] Li, Donglin, Jiacan Xu, Jianhui Wang, Xiaoke Fang, and Ying Ji. "A multi-scale fusion convolutional neural network based on attention mechanism for the visualization analysis of EEG signals decoding." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 28, no. 12 (2020): 2615-2626.
- [5] Wang, Yan, Xixuan Feng, Liping Song, Xiangbin Liu, and Shuai Liu. "Multiclassification of endoscopic colonoscopy images based on deep transfer learning." *Computational and Mathematical Methods in Medicine* 2021 (2021).
- [6] Tanwar, Sushama, and S. Vijayalakshmi. "Comparative analysis and proposal of deep learning based colorectal cancer polyps classification technique." *Journal of Computational and Theoretical Nanoscience* 17, no. 5 (2020): 2354-2362.
- [7] Gour, Neha, and Pritee Khanna. "Multi-class multi-label ophthalmological disease detection using transfer learning based convolutional neural network." *Biomedical Signal Processing and Control* 66 (2021): 102329.
- [8] Huang, Kaimei, Binghu Lin, Jinyang Liu, Yankun Liu, Jingwu Li, Geng Tian, and Jialiang Yang. "Predicting colorectal cancer tumor mutational burden from histopathological images and clinical information using multi-modal deep learning." *Bioinformatics* 38, no. 22 (2022): 5108-5115.
- [9] Dabass, Manju, Sharda Vashisth, and Rekha Vig. "A convolution neural network with multi-level convolutional and attention learning for classification of cancer grades and tissue structures in colon histopathological images." *Computers in biology and medicine* 147 (2022): 105680.
- [10] Bray, Freddie, Jacques Ferlay, Isabelle Soerjomataram, Rebecca L. Siegel, Lindsey A. Torre, and Ahmedin Jemal. "Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries." *CA: a cancer journal for clinicians* 68, no. 6 (2018): 394-424.
- [11] Liang, Meiyan, Ru Wang, Jianan Liang, Lin Wang, Bo Li, Xiaojun Jia, Yu Zhang, Qinghui Chen, Tianyi Zhang, and Cunlin Zhang. "Interpretable Inference and Classification of Tissue Types in Histological Colorectal Cancer Slides Based on Ensembles Adaptive Boosting Prototype Tree." *IEEE Journal of Biomedical and Health Informatics* (2023).
- [12] Mukhlif, Abdulrahman Abbas, Belal Al-Khateeb, and Mazin Abed Mohammed. "An extensive review of state-of-the-art transfer learning techniques used in medical imaging: Open issues and challenges." *Journal of Intelligent Systems* 31, no. 1 (2022): 1085-1111.
- [13] Morid, Mohammad Amin, Alireza Borjali, and Guilherme Del Fiol. "A scoping review of transfer learning research on medical image analysis using ImageNet." *Computers in biology and medicine* 128 (2021): 104115.
- [14] Hamida, A. Ben, Maxime Devanne, Jonathan Weber, Caroline Truntzer, Valentin Derangère, François Ghiringhelli, Germain Forestier, and Cédric Wemmert. "Deep learning for colon cancer histopathological images analysis." *Computers in Biology and Medicine* 136 (2021): 104730.
- [15] Chen, Haoyuan, Chen Li, Xiaoyan Li, Md Mamunur Rahaman, Weiming Hu, Yixin Li, Wanli Liu et al. "IL-MCAM: An interactive learning and multi-channel attention mechanism-based weakly supervised colorectal histopathology image classification approach." *Computers in Biology and Medicine* 143 (2022): 105265.
- [16] Kather, Jakob Nikolas, Frank Gerrit Zöllner, Francesco Bianconi, Susanne M. Melchers, Lothar R. Schad, Timo Gaiser, Alexander Marx, and Cleo-Aron Weis. "Collection of textures in colorectal cancer histology." *Zenodo* <https://doi.org/10.5281/2016> (2016).



Shah Muhammad Imtiyaz Uddin is pursuing his Master's in the Institute of Digital Anti-Aging Healthcare from Inje University. He has previously worked on multiple real-life projects related to mobile applications, computer vision, data sciences, and user interface systems. His research interest aligns with Computer Vision, Artificial Intelligence, and mobile applications.



Md Ariful Islam Mozumder is pursuing his Master's in the Institute of Digital Anti-Aging Healthcare from Inje University. He has previously worked on multiple real-life projects related to computer vision, data sciences, Smart IoT systems, and Natural Language Processing. His research interest aligns with Computer Vision, Artificial Intelligence, Bio Signal Processing, Algorithms, and Metaverse.



Rashedul Islam Sumon is pursuing his Master's in the Institute of Digital Anti-Aging Healthcare from Inje University. He has previously worked on multiple real-life projects related to computer vision, data sciences, Smart IoT systems, and text mining. His research interest aligns with Computer Vision, Artificial Intelligence, Medical Image Processing, Algorithms, and Natural Language Processing.



Moon-Il Joo received a PhD degree in computer engineering from Inje University in 2018. He is currently working as a research professor at the Institute of digital anti-aging Healthcare, Inje University, Korea. His research interests are in software engineering, human-computer-computer interaction, smartphone programming, and component-based development.



Hee-Cheol Kim BSc at the Department of Mathematics, MSc at the Department of Computer Science at SoGang University in Korea, and Ph.D. in Numerical Analysis and Computing Science, at Stockholm University in Sweden. He is a professor and Head of the Department of the Institute. Digital Anti-aging Healthcare, Inje University, S: Korea. His research interests include Machine learning, Text mining, Bioinformatics, Metaverse, Natural Language Processing, and Smart Logistics.