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Fully automated tumor-stroma ratio prediction as prognosis factor in colorectal cancer using optimized deep transfer learning

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Abstract: The Tumor-Stroma Ratio (TSR) reflects a higher ratio of stromal cells compared to cancer cells in a tumor, which is associated with a worse prognosis, increased risk of recurrence, and reduced overall survival in colorectal cancer. This paper reports the application of optimized deep transfer learning for fully automated tumor-stroma ratio estimation and its significance as a prognostic factor in patient survival prediction. Various base models of transfer learning, including ResNet18, DenseNet201, MobileNet_V2, EfficientNet_b2, and Inception_V3, are considered. All base models were trained using the Optuna hyperparameter optimization framework, which is flexible, modular, and easy to combine with transfer learning. After determining the optimal deep transfer learning model, it was implemented to predict the tumor-stroma ratio (TSR). Experimental comparisons indicate that ResNet18 is the most suitable base deep transfer learning model for colorectal cancer (CRC) classification. Consequently, ResNet18 was used to classify whole slide images of colorectal patients. Finally, the Cox proportional hazards model was applied to features including TSR and other clinical parameters of colorectal cancer. The results demonstrate that the Tumor-Stroma Ratio can be considered an important prognostic factor for colorectal cancer based on survival analysis prediction.

Keywords: *Colorectal cancer, Convolutional neural networks, Deep transfer learning, Patient survival, Tumor-stroma ratio.*

1. Introduction

As widely known, colorectal cancer (CRC) is the fourth most common form of cancer and the second deadliest disease [1]. Furthermore, according to the American Institute of Cancer Research, colorectal cancer cases worldwide are expected to increase by 60 percent over the next fifteen years. Therefore, the critical steps for diagnosis will also rise rapidly, which could prove disastrous if pathologists rely solely on manual examinations [2].

With the advancement in the field of Artificial Intelligence, including several Deep Learning approaches, it has been applied to identify biomarkers in colorectal carcinoma cancer [3, 4]. The advantages of deep learning-based approaches can be used as a solid 'feature extractor' for slides of cancer composition. Then, those extracted features will be determined using a well-defined feature selection technique. Finally, a classifier technique will decompose slide images into their expected category of colorectal carcinoma (CRC) [5-8].

Various architectures of Convolutional Neural Networks (CNN) have been developed, such as Deep Residual Networks (ResNet), Inception Networks, Densely Connected Convolutional Networks (DenseNet), MobileNet, and EfficientNet [9]. Those architectures are usually implemented in image classification within the transfer learning framework [10] in which knowledge learned from a task is re-used in order to boost performance on a related task. The transfer learning framework simply uses the "pre-trained weight" CNN-based model architecture using related image datasets. All the base models were

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trained using the Optuna hyperparameter optimization framework [11], which has flexible, modular, and easy-to-combine with transfer learning.

Having determined the optimized deep transfer learning, the model will be deployed on the training and test data sets to classify nine classes of colorectal carcinoma slide images, including tumor and stroma classes. The best model will be applied to Whole Slide Images (WSI) to identify areas of tumor and stroma. In tumors, the stroma is non-cancerous tissue, which includes fibroblasts, blood vessels, and immune cells, forming the tumor microenvironment [12, 13]. It's mostly a product of the host and is very important for tumor growth, development, invasion, and metastasis. Therefore, the Tumor-Stroma Ratio (TSR) is a prognostic indicator in cancer, defined as the proportion of stroma (non-cancerous cells and extracellular matrix) to cancer cells within a tumor [13, 14]. A high TSR, meaning higher percentages of stroma, is generally associated with a poorer prognosis, shorter survival, and increased risk of recurrence and metastasis in many cancers, including colorectal cancer. Pathologists determine TSR visually by following a certain scoring protocol. The main problem with this approach is the reproducibility and consistency of the TSR scoring. Therefore, developing an automated TSR scoring system is required to ensure that the values are reproducible and consistent [12, 14-16].

The automated prediction of TSR will be computed based on whole slide images for each patient using the optimized deep transfer learning methods identified in the previous steps. Those TSR values will be included as prognostic factors alongside clinical factors of CRC, such as gender, age, T-stage, and M-stage. Finally, a patient survival prediction model, called the Cox proportional hazards (Cox-PH) model, will be developed. From the Cox-PH model, the significance of TSR as a prognostic factor will be analyzed [10].

This study has two contributions: first, this research can provide insights to medical experts and computer scientists regarding the current state of development of deep transfer learning approaches for histopathological image classification, especially in colorectal carcinoma (CRC). The second contribution of this research is to propose a fully automatic tumor-stroma prediction as a prognostic factor for colorectal cancer.

The goals of the paper can be summarized in two main points: firstly, a fully automated scoring system for TSR prediction will be proposed. Secondly, the significance of TSR as a prognostic factor, alongside other clinical factors such as gender, age, and T-stage in colorectal cancer, will be evaluated using the Cox proportional hazards (Cox-PH) model.

To achieve the goals, this paper will be organized as follows. First, Deep Transfer Learning of the CNN-based model for the classification of CRC will be explored. The hyperparameter optimization for the transfer learning model will be reviewed. Then, the experimental settings for finding the tumor-stroma ratio will be described. The results and discussions will present some findings of the experiments. The paper will be concluded by summarizing the findings, suggestions, and further work.

2. Optimized Deep Transfer Learning

Transfer learning is a machine learning framework in which knowledge obtained through one task or dataset is reused to enhance model performance on another related task and/or a different dataset [17].

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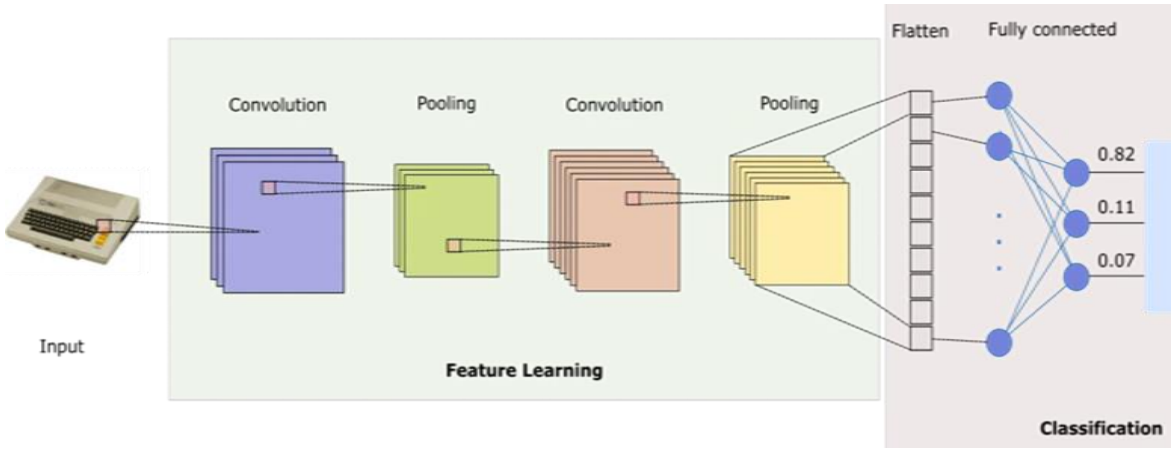

Figure 1.
A simple CNN architecture.

Deep transfer learning is a type of transfer learning used for training deep learning models. In this paper, the architecture of Convolutional Neural Networks (CNN) will be used to extract image features of colorectal cancer patients, as shown in Figure 2.

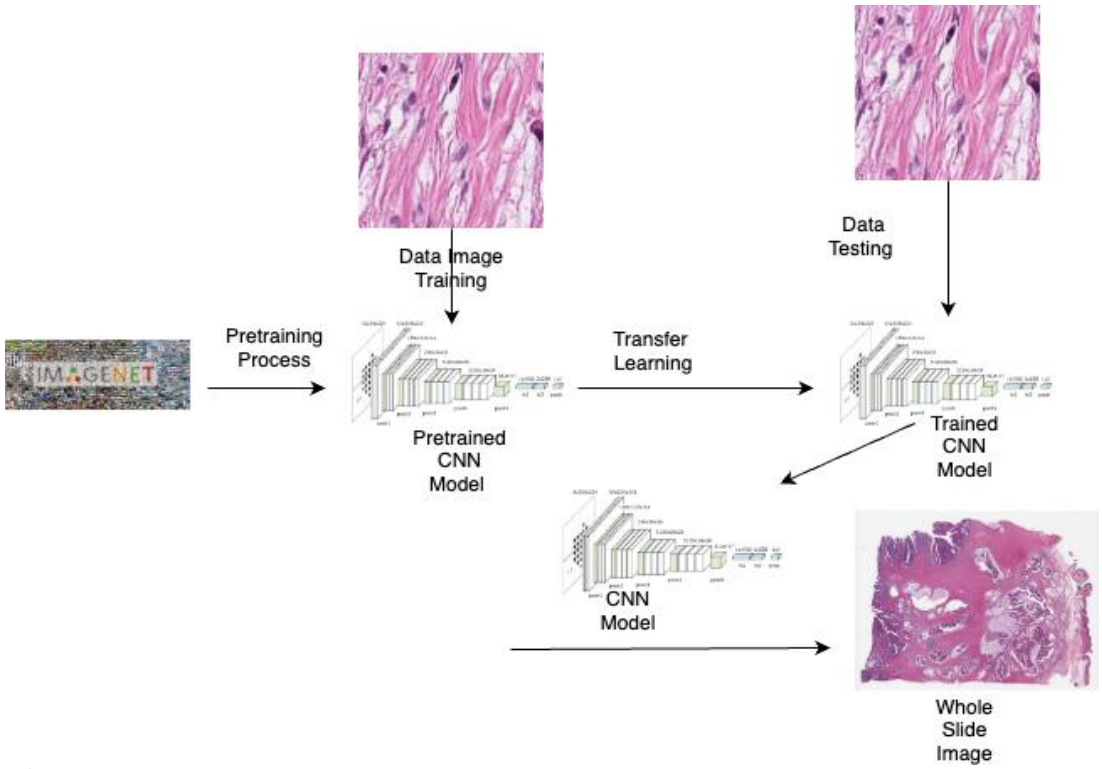

Figure 2.
Deep Transfer Learning for Patients' Cancer Image Classification.

Transfer learning methods in deep learning aim to reduce the cost and training time, as well as the necessity of extensive training datasets, which can be difficult to obtain in some areas, such as colorectal carcinoma slide images. In this work, five CNN-based models, ResNet50, Inception_v3, DenseNet201, EfficientNet_b2, and MobileNetV2, will be explored and their performances compared using real

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colorectal carcinoma image datasets. The parameters of the models will be optimized using the Optuna algorithm [11]. The transfer learning usually uses weights from the pretrained model on the Imagenet data sets [10, 15].

3. Hyperparameter Optimization (HPO)

Despite the achievements of Deep Learning in various applications, the design and training of Deep Learning models remain challenging and uncontrolled processes that are often associated with uncertainty. To reduce the technical barriers for naive users, automated hyper-parameter optimization (HPO) has become a trending topic in both academic and industrial sectors. Currently, there are four main approaches to implementing hyper-parameter optimization, including [18]: Grid Search, Random Search, Bayesian Optimization, and the Optuna framework. The approaches will be briefly explored as follows:

3.1. Grid Search

Grid search is one of the most widely implemented hyperparameter optimization approaches. It operates by exhaustively searching through all possible combinations of hyperparameters within a specified grid. This method guarantees that every candidate combination is considered, ensuring that the best set of hyperparameters within the defined grid is identified.

3.2. Random Search

Instead of intensively searching through every possible combination of hyperparameters, random search collects a fixed number of random combinations from the search space. This allows random search to explore the hyperparameter space more efficiently, often yielding good results with fewer iterations.

3.3. Bayes Optimization

Bayesian Optimization is an advanced and efficient method that determines the probabilistic relationship between hyperparameters and the objective function, usually employing a Gaussian Process (GP) model. The objective is to search for the optimal hyperparameters by selecting the next set of hyperparameters to evaluate based on the results of previous evaluations.

3.4. Optuna: A Hyperparameter Optimization Framework

More recent approaches in hyperparameter optimization include Optuna, which is defined as an automatic hyperparameter optimization software framework (18). It features an imperative, define-by-run style user Application Programming Interface (API). The program written with Optuna benefits from high modularity, and the user can dynamically develop the search spaces for the hyperparameters. This paper will use this approach based on considerations of flexibility, modularity, and ease of integration with transfer learning frameworks [11, 18, 19].

4. Prognostic Model

Prognostic models are defined as frameworks that use clinical parameters, such as gender, gestational age, and stage of cancer, to categorize patients into different prognostic categories. It would be useful in aiding decision-making regarding the level of care, especially in contexts like colorectal cancer. These models determine the probability of acceptable outcomes, highlighting the importance of evaluating new models against existing ones. In this paper, to determine the tumor-stroma ratio as a prognostic factor in colorectal cancer, it will be included in the prognostic model, especially in the Cox proportional-hazard model [10].

4.1. Cox Proportional-Hazards Model

The Cox proportional-hazards model is essentially a regression model commonly used in medical research to determine the association between patients' survival time and one or more prognostic factors,

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such as age, gender, M-stage, and T-stage in colorectal cancer [5, 10, 15]. In this paper, the tumor-stroma ratio (TSR) will be included as a new prognostic factor in colorectal cancer. The importance of TSR can be determined from the significance of the coefficients of the model.

4.2. Kaplan-Meier Survival Analysis

Kaplan-Meier survival analysis is a statistical method for estimating survival predictions from lifetime patient data and is represented by a stepwise decreasing curve, plotting survival probability on the Y-axis against time on the X-axis. In this paper, the high tumor-stroma ratio (high-TSR) and low tumor-stroma ratio (low-TSR) will be shown using Kaplan-Meier survival analysis.

Tumors with a high proportion of stroma (often defined as >50%) are considered "high-TSR," while those with abundant carcinoma tissue (≤50% stroma) are "low-TSR." The high-TSR is generally associated with a poorer prognosis, shorter survival, and increased risk of recurrence and metastasis in many cancers, including colorectal cancer.

5. Experimental Settings

5.1. Data Description

The training and test data set can be downloaded in the following publicly open website [15]: https://zenodo.org/records/4024676

This downloaded colorectal carcinoma data set consists of the training set used to train the CNN model, including 283,100 image patches, including HE slides of CRC tissue randomly selected from those retrieved from The Cancer Genome Atlas. Two independent test sets (test sets 1 and 2) were used to assess the classification performance of the trained CNN model. Non-overlapping image patches from hematoxylin & eosin (H&E) stained histological images of human colorectal cancer (CRC) and normal tissue were included [20]. There are 9 tissue classes: Adipose (ADI), background (BACK), debris (DEB), lymphocytes (LYM), mucus (MUC), smooth muscle (MUS), normal colon mucosa (NORM), cancer-associated stroma (STR), colorectal adenocarcinoma epithelium (TUM). LYM, STR, and TUM classes have important roles in colorectal carcinoma. Especially, TUM and STR are used to determine the Tumor-Stroma Ratio (TSR).

5.2. Optimized Deep Transfer Learning for Tumor-Stroma Ratio Prediction

Five base CNN models, including ResNet18, DenseNet201, Inception_v3, EfficientB2, and MobileNetV2, were trained on training data sets [19, 21]. The training process used Optuna hyperparameter optimization 20 epochs and 3 trials.

Having determined the best CNN model with Optuna hyperparameter optimization, the next step is to apply the model to predict on the whole slide images dataset for each colorectal cancer patient. The outcome of the prediction will be used to calculate the area of tumor (TUM) and stroma (STR). Finally, the tumor-stroma ratio in colorectal cancer can be predicted.

5.3. The evaluation of Tumor-Stroma Ratio (TSR) as a Prognosis Factor in Colorectal Cancer

The importance of TSR with other clinical parameters, such as age, gender, and M-stage as prognostic factors in colorectal cancer and others will be determined using the Cox proportional-hazards model. Then, patient survival prediction for high-TSR and low-TSR groups will be shown by the Kaplan-Meier curve.

Overall, experimental settings can be shown in the following figure:

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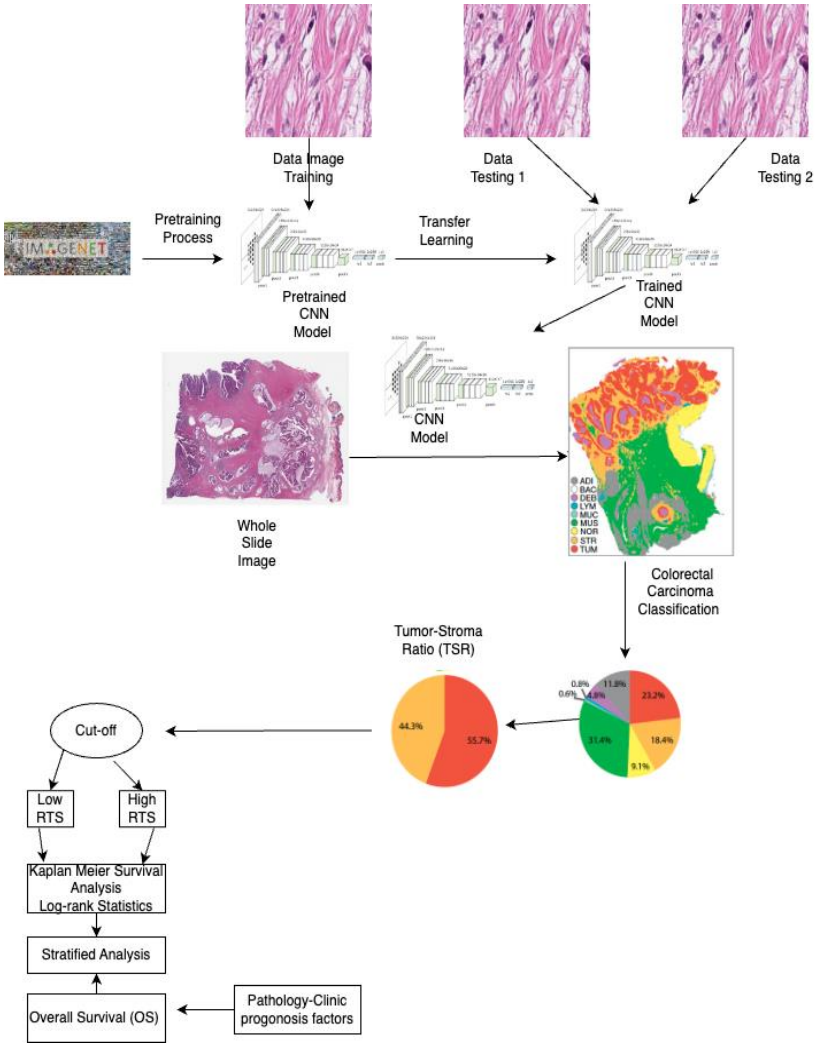

Figure 3.
Flow of Experimental Settings.

6. Results and Discussions

6.1. Optimized Base Model Deep Transfer Learning

To achieve high training accuracy of the base models, Optuna hyperparameter optimization will be implemented. Some hyperparameters include learning rate (lr), batch size, optimizer types (Adam or stochastic gradient descent), and weight decay (L2 regularization). The optimal value of the hyperparameter combination will produce the highest accuracy with reasonable speed. Each base model has a different combination of optimal hyperparameters, as shown in Figure 4. The performance of ResNet18, DenseNet201, and EfficientNet_b2 is mainly influenced by weight decay (L2 regularization), whereas Inception_V3 relies on the learning rate, and MobileNetV2 depends on batch size.

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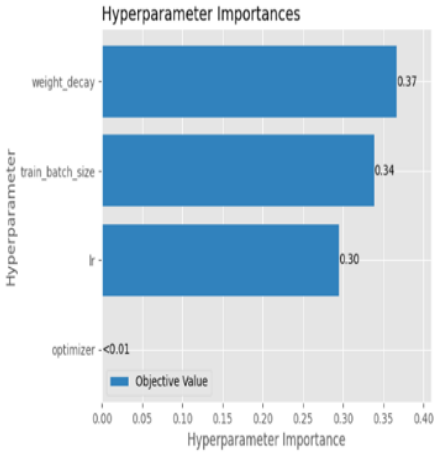
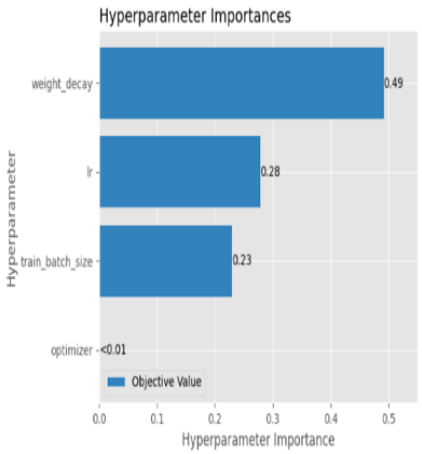
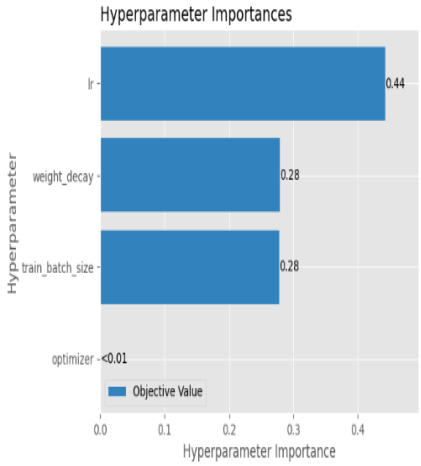


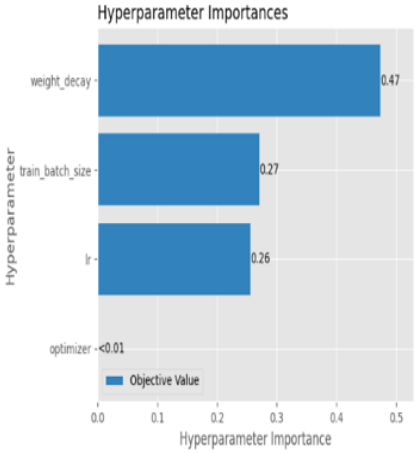
Hyperparameter Importance of Resnet18



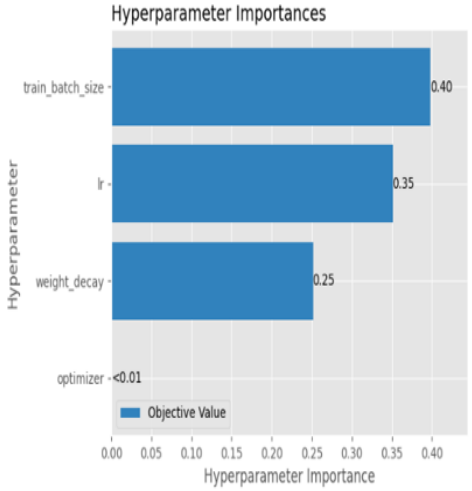
Hyperparameter Importance of Desnet201



Hyperparameter Importance of Inception_V3



Hyperparameter Importance of EfficientNetb2



Hyperparameter Importance of Mobilenet_V2

Figure 4.
The hyperparameter importance on base models ResNet18, DenseNet 201, Inception V3, EfficientNet B2, and MobileNet V2.

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The five CNN base models will be evaluated on the test-1 and test-2 datasets. The table shows the results of the experiments. Overall, ResNet-18 produced the highest accuracy and the fastest computation, based on batch size and learning rate, which are 44 and 0.00004, respectively. The second best was achieved by EfficientNet_b2, followed by Inception_V3 and Densenet201. MobileNet_V2 is the worst base CNN model.

Table 1.
Test the accuracy of base models of ResNet18, DenseNet-201, Inception_V3, EfficientNet_B2, and MobileNet_V2 using Optuna hyperparameter optimization.

Base Model	Test-1 ACC (%)	Test-2	Learning Rate	Batch Size	Weight Decay	Optimizer	Time (Min)
Resnet18	99.99	98.16	0.00004	44	0.000008	Adam	53.57
Densenet201	99.99	97.23	0.00003	27	0.000001	Adam	156.25
Inception_v3	99.99	98.12	0.00002	16	0.000002	Adam	79.38
Efficientnet_b2	99.99	98.13	0.00008	29	0.000003	Adam	67.57
MobilenetV2	98.98	96.12	0.00006	24	0.000003	Adam	61.67

Based on the test accuracy shown in Table 1, the base model CNN ResNet18 provides the highest and most consistent accuracy, as well as the fastest computation. Therefore, for further analysis, the ResNet base models will be implemented in subsequent steps. The model to be identified through Optuna hyperparameter optimization will then be used to classify external data, as shown in Figure 5. The probability of the model's classification is computed using a softmax classifier.

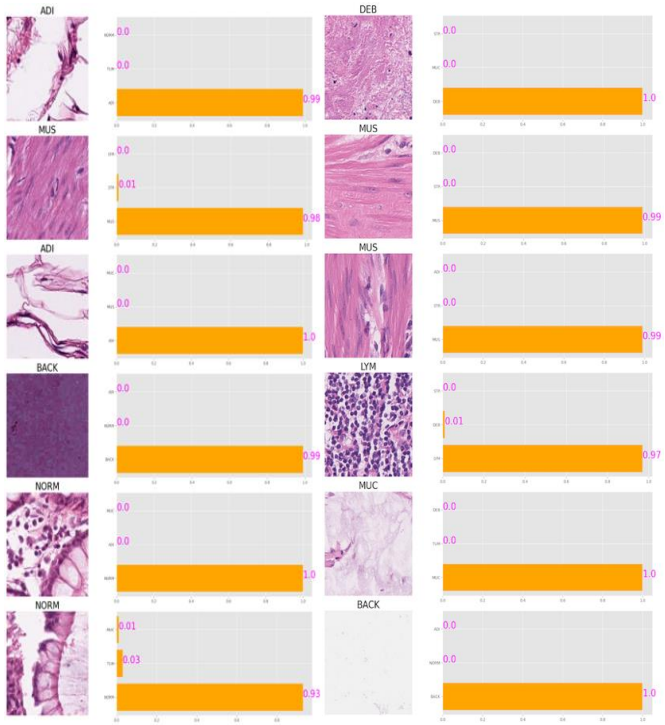

Figure 5.
The probability of the Resnet 18 model to classify the test data 1 (left) and test data 2 (right) in the correct classes.

As shown in Fig5, the ResNet18 performed well on both test datasets. The model can predict the class of images with a probability higher than 98%. For model deployment, the newer versions of ResNet,

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ResNet50, will be used. It is evident that the newer model has a more complex structure than ResNet18. Therefore, the performance of the ResNet50 model is expected to be better than that of ResNet18.

6.2. Model Deployment for TSR Prediction

The ResNet50, the updated version of ResNet18, is deployed on whole slide images (WSI) of colorectal cancer patients. The nine classes of colorectal carcinoma have been successfully classified by ResNet 50. The sample heatmap of the classes is shown in Figure 5. The TUM class has the highest proportion compared to the other classes. Near the TUM, there are STR classes. These TUM and STR classes indicate the level of prognosis of colorectal carcinoma. If the proportion of TUM and STR exceeds 0.5, this ratio is considered a high Tumor-Stroma Ratio (TSR), which indicates a larger proportion of stroma compared to tumor cells. This suggests a more aggressive tumor biology and is a potential prognostic factor, indicating a need for more intensive treatment strategies.

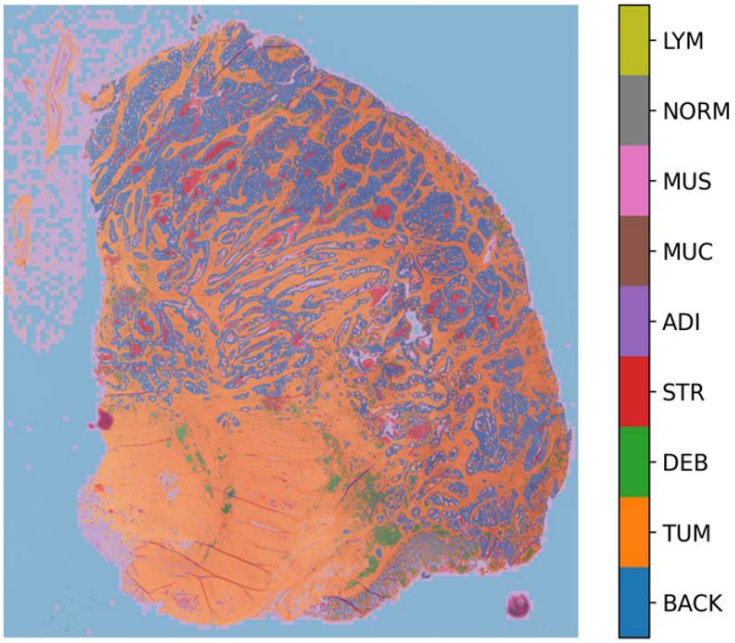

Figure 6.
The heatmap of colorectal carcinoma.

The example of the proportion of nine classes of colorectal carcinoma is shown in Figure 6. After determining the classification heatmap, the areas of TUM and STR will be identified. Subsequently, the Tumor-Stroma ratio can be calculated as follows:

$$TSR = \frac{L_{STR}}{(L_{STR} + L_{TUM})} \qquad (1)$$

Where TSR, L_{STR}, and L_{TUM} are the Tumor-Stroma Ratio, area of Stroma, and area of Tumor, respectively. If the TSR > 0.5, it is called a high TSR; otherwise, it is called a low TSR.

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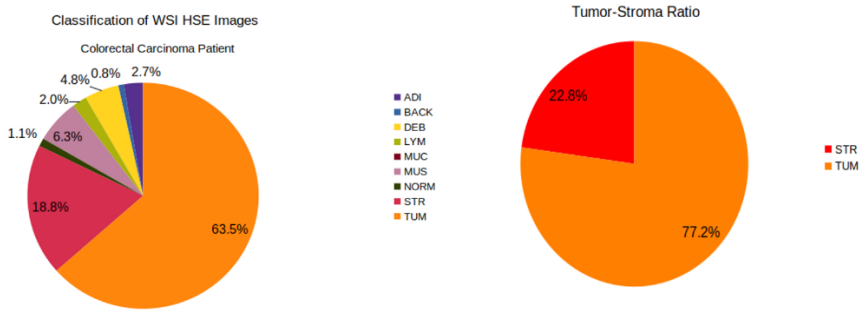

Figure 7.
The example of the proportion of nine classes of colorectal carcinoma and the TSR prediction.

The sample of the TSR value is shown in Figure 7. First, the overall prediction classes determined by ResNet50 are shown in the figure above. From the overall classes, the tumor classes and stroma classes will be extracted. Then, the areas of TUM and STR will be determined. Finally, the TSR value can be predicted using Equation (1).

6.3. Evaluation of TSR as a Prognosis Factor in CRC

For the evaluation of TSR as a prognostic factor in colorectal cancer, we used The Cancer Genome Atlas (TCGA) Colorectal Adenocarcinoma (COAD) data from (). As shown in Table 2, a sample of 222 patients' data has been used to determine the importance of TSR as a prognostic factor in colorectal cancer using the *Cox proportional-hazards model.*

Table 2.
Sample TGCA Colorectal Measurement Data.

Years_to birth	Event	Pathologic stage	Pathology T_stage	Pathology M_stage	Gender	Time	TSR
74	TRUE	Stage iv	t3	m1b	Male	49	High
40	TRUE	Stage iv	t4a	m1a	Female	290	Low
85	TRUE	Stage iv	t3	m1	Male	1331	Low
70	TRUE	Stage iv	t4b	m1	Male	424	Low
53	FALSE	Stage iiic	t3	m0	Female	1054	Low
80	FALSE	Stage iiic	t4a	mx	Male	672	Low
60	FALSE	Stage iia	t3	m0	Male	1186	Low
89	FALSE	Stage iiib	t3	m0	Male	245	Low
57	FALSE	Stage i	t2	m0	Male	580	Low

Table 3.
The Significance of Prognosis Factor Model.

TSR	1.02	2.774	0.464	2.199	0.028	0.028
pathology_T_stage_t2	15.991	8807620.074	3137.135	0.005	0.996	0.996
pathology_T_stage_t3	16.289	1858763.221	3137.135	0.005	0.996	0.996
pathology_T_stage_t4	15.778	7115416.985	3137.135	0.005	0.996	0.996
pathology_T_stage_t4a	16.032	9174120.975	3137.135	0.005	0.996	0.996
pathology_T_stage_t4b	17.827	55248235.93	3137.135	0.006	0.995	0.996
pathology_M_stage_m1	1.878	6.544	0.407	4.61	0	0
pathology_M_stage_m1a	1.489	4.433	1.186	1.255	0.209	0.209
pathology_M_stage_m1b	3.077	21.695	1.152	2.671	0.008	0.008
pathology_M_stage_mx	-0.407	0.666	1.053	-0.386	0.699	0.699

The results are shown in Table 3. There are four main prognostic factors that play an important role in patient survival prediction, which include *pathology_M_stage_m1*, *Tumor-Stroma Ratio (TSR)*,

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pathology_M_stage_m1b, and *gender*. The model has a Concordance index of 0.79. As expected, TSR is one of the significant prognostic factors in colorectal cancer, with a P-value of 0.028.

For further analysis, the two class categories, low-TSR and high-TSR, will be determined to assess whether both categories have a significant difference in patient survival prediction, as shown in Figure 8. The TSR=1 and TSR=0 refer to high TSR and low TSR, respectively. The results show that the two classes have very different survival probabilities, with the low TSR tending to have a higher probability than the high TSR. Thus, the TSR values identified by deep transfer learning play an important role in patient survival prediction.

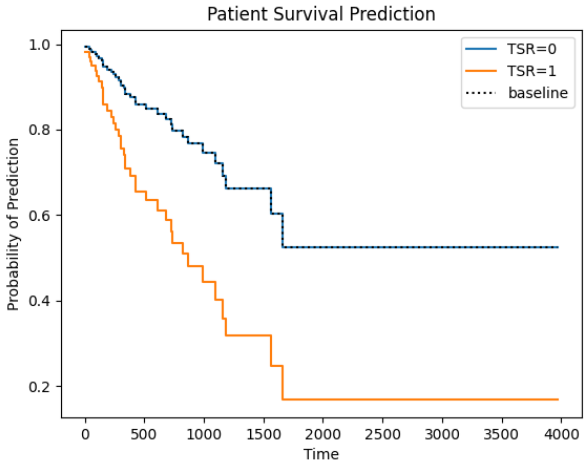

Figure 8.
Patient Survival Prediction on High-TSR(1) and Low-TSR (0).

7. Conclusions

The applications of various architectures of Convolutional Neural Networks (CNN), such as Deep Residual Networks (ResNet), Inception Networks, Densely Connected Convolutional Networks (DenseNet), MobileNet, and EfficientNet, for colorectal cancer image classification and automated Tumor-Stroma Ratio (TSR) prediction have been successfully implemented. In the proposed framework, all the base models were trained using the Optuna hyperparameter optimization framework, which is flexible, modular, and easy to combine with transfer learning.

Results show that the optimized ResNet base model outperformed the other base models using Optuna hyperparameter optimization. The classification accuracy of the optimized ResNet50 base model achieved more than 98% on external test data.

The optimized ResNet50 is used to classify whole slide images (WSI) of colorectal patients, which allows for the prediction of the tumor-stroma ratio (TSR). ResNet50 was applied to 222 WSI patients, resulting in 222 TSR values. These TSR values, along with other clinical parameters such as M-stage, T-stage, age, and gender, were included in the Cox proportional hazards model to predict patient survival. The results indicate that TSR is a prognostic factor in colorectal cancer. Overall, the TSR levels, categorized as High-TSR and Low-TSR, are associated with different probabilities of patient survival.

In future works, this automated TSR approach can be compared using the real data sets that are created by pathologists. Those comparisons should be carried out carefully, which depend on many considerations such as the quality of images, the structure of images, and the similarity of the environment when the images are obtained.

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Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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References

[1] Colorectal Cancer Alliance, "Colorectal cancer information," 2025. https://colorectalcancer.org/

[2] World Cancer Research Fund/American Institute for Cancer Research, "Diet, nutrition, physical activity and cancer: A global perspective. Continuous Update Project Expert Report," 2018. https://www.wcrf.org/diet-activity-and-cancer/

[3] F. Prezja *et al.*, "Improved accuracy in colorectal cancer tissue decomposition through refinement of established deep learning solutions," *Scientific Reports*, vol. 13, p. 15879, 2023. https://doi.org/10.1038/s41598-023-42357-x

[4] S. H. Lee and H.-J. Jang, "Deep learning-based prediction of molecular cancer biomarkers from tissue slides: A new tool for precision oncology," *Clinical and Molecular Hepatology*, vol. 28, no. 4, p. 754, 2022. https://doi.org/10.3350/cmh.2021.0394

[5] J. N. Kather *et al.*, "Predicting survival from colorectal cancer histology slides using deep learning: A retrospective multicenter study," *PLoS Medicine*, vol. 16, no. 1, p. e1002730, 2019. https://doi.org/10.1371/journal.pmed.1002730

[6] M. Lee, "Recent advancements in deep learning using whole slide imaging for cancer prognosis," *Bioengineering*, vol. 10, no. 8, p. 897, 2023.

[7] V. B. Mathema, P. Sen, S. Lamichhane, M. Orešič, and S. Khoomrung, "Deep learning facilitates multi-data type analysis and predictive biomarker discovery in cancer precision medicine," *Computational and Structural Biotechnology Journal*, vol. 21, pp. 1372-1382, 2023. https://doi.org/10.1016/j.csbj.2023.01.043

[8] M. F. Ijaz and M. Woźniak, "Recent advances in deep learning and medical imaging for cancer treatment," vol. 16, ed: MDPI, 2024, p. 700.

[9] L. Alzubaidi *et al.*, "Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions," *Journal of Big Data*, vol. 8, p. 53, 2021. https://doi.org/10.1186/s40537-021-00444-8

[10] J. L. Katzman, U. Shaham, A. Cloninger, J. Bates, T. Jiang, and Y. Kluger, "DeepSurv: Personalized treatment recommender system using a Cox proportional hazards deep neural network," *BMC Medical Research Methodology*, vol. 18, p. 24, 2018. https://doi.org/10.1186/s12874-018-0482-1

[11] T. Akiba, S. Sano, T. Yanase, T. Ohta, and M. Koyama, "Optuna: A next-generation hyperparameter optimization framework," in *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 2019.

[12] M. A. Smit *et al.*, "Deep learning based tumor–stroma ratio scoring in colon cancer correlates with microscopic assessment," *Journal of Pathology Informatics*, vol. 14, p. 100191, 2023. https://doi.org/10.1016/j.jpi.2023.100191

[13] J. Gao, Z. Shen, Z. Deng, and L. Mei, "Impact of tumor–stroma ratio on the prognosis of colorectal cancer: A systematic review," *Frontiers in Oncology*, vol. 11, p. 738080, 2021. https://doi.org/10.3389/fonc.2021.738080

[14] L. Petäinen, J. P. Väyrynen, P. Ruusuvuori, I. Pölönen, S. Äyrämö, and T. Kuopio, "Domain-specific transfer learning in the automated scoring of tumor-stroma ratio from histopathological images of colorectal cancer," *Plos One*, vol. 18, no. 5, p. e0286270, 2023. https://doi.org/10.1371/journal.pone.0286270

[15] K. Zhao *et al.*, "Artificial intelligence quantified tumour-stroma ratio is an independent predictor for overall survival in resectable colorectal cancer," *EBioMedicine*, vol. 61, p. 103054, 2020. https://doi.org/10.1016/j.ebiom.2020.103054

[16] D. Firmbach *et al.*, "Tumor–stroma ratio in colorectal cancer—comparison between human estimation and automated assessment," *Cancers*, vol. 15, no. 10, p. 2675, 2023. https://doi.org/10.3390/cancers15102675

[17] H. E. Kim, A. Cosa-Linan, N. Santhanam, M. Jannesari, M. E. Maros, and T. Ganslandt, "Transfer learning for medical image classification: A literature review," *BMC Medical Imaging*, vol. 22, p. 69, 2022. https://doi.org/10.1186/s12880-022-00793-7

[18] M. A. K. Raiaan *et al.*, "A systematic review of hyperparameter optimization techniques in convolutional neural networks," *Decision Analytics Journal*, vol. 11, p. 100470, 2024. https://doi.org/10.1016/j.dajour.2024.100470

[19] M. Iman, H. R. Arabnia, and K. Rasheed, "A review of deep transfer learning and recent advancements," *Technologies*, vol. 11, no. 2, p. 40, 2023.
[20] M. Khazaee Fadafen and K. Rezaee, "Ensemble-based multi-tissue classification approach of colorectal cancer histology images using a novel hybrid deep learning framework," *Scientific Reports*, vol. 13, no. 1, p. 8823, 2023. https://doi.org/10.1038/s41598-023-35431-x
[21] M. Yildirim and A. Cinar, "Classification with respect to colon adenocarcinoma and colon benign tissue of colon histopathological images with a new CNN model: MA_ColonNET," *International Journal of Imaging Systems and Technology*, vol. 32, no. 1, pp. 155-162, 2022. https://doi.org/10.1002/ima.22623

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