

Ensemble of Handcrafted and Learned Features using a Lightweight CNN for Colorectal Cancer Classification

Combinação de Características Manuais e Aprendidas usando uma CNN Leve para Classificação de Câncer Colorretal

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Abstract: Colorectal cancer (CRC) is one of the highest incident cancers in the world. The late-stage diagnosis plays a pivotal role in the mortality rate, making CRC the second leading cause of cancer-related deaths. Its diagnosis is based on the analysis of histological images acquired from a biopsy, a time-consuming and prone to errors task. Over the years, many deep learning and computer vision approaches have been proposed to automatize such a task, reducing the need for human specialists. To contribute to this area of research, we proposed an ensemble that combines a Lightweight CNN and handcrafted color texture features commonly used in literature. We investigated how different texture methods impact the performance of the ensemble in an important multi-class problem composed of eight types of tissues. Our ensemble obtained 99.63% accuracy, surpassing state of the art methods and deeper CNNs, and 99.63% F1 score, showing a good balance between precision and recall.

Keywords: colorectal cancer — histological images — lightweight CNN — texture features — ensemble learning

Resumo: O câncer colorretal (CRC) está entre os de maior incidência no mundo. O diagnóstico em estágio avançado desempenha um papel crucial na taxa de mortalidade, tornando o CRC a segunda principal causa de mortes relacionadas ao câncer. Seu diagnóstico baseia-se na análise de imagens histológicas obtidas por biópsia, uma tarefa demorada e suscetível a erros. Ao longo dos anos, diversas abordagens de aprendizado profundo e visão computacional foram propostas para automatizar essa tarefa, reduzindo a necessidade de especialistas humanos. Para contribuir com essa área de pesquisa, propusemos um ensemble que combina uma CNN leve e características de textura de cor artesanalmente extraídas, comumente utilizadas na literatura. Investigamos como diferentes métodos de textura impactam o desempenho do ensemble em um importante problema de classificação multiclasse composto por oito tipos de tecidos. Nosso ensemble obteve 99,63% de acurácia, superando métodos do estado da arte e CNNs mais profundas, além de alcançar 99,63% de F1-score, demonstrando um bom equilíbrio entre precisão e recall.

Palavras-Chave: câncer colorretal — imagens histológicas — CNN leve — características de textura — aprendizado em conjunto

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1. Introduction

Colorectal cancer (CRC) is one of the most prevalent and lethal malignancies worldwide, ranking as the third most common cancer and second leading cause of cancer-related deaths. Its high mortality rate is largely due to late-stage diagnoses, where survival rates drop significantly compared with early detection. The disease originates from the malignant transformation of colorectal polyps and is influenced by genetic, environmental, and lifestyle factors [1][2]. While early

and accurate detection is crucial for improving patient outcomes, traditional diagnostic methods, such as colonoscopy and histopathological analysis, face challenges related to interpretation variability and time-consuming procedures [3].

Artificial Intelligence (AI) and Computer Vision techniques have become essential for medical image analysis, providing advanced solutions for computer-aided diagnosis. Although Convolutional Neural Networks (CNNs), Transformers, and generative models achieve high accuracy in CRC

histopathology classification, their computational demands render them difficult to implement in clinical settings [3][4]. On the other hand, handcrafted features (i.e., features that are explicitly designed based on domain knowledge, rather than learned through deep learning) such as Local Binary Pattern (LBP) and Haralick texture descriptors have long been used in medical imaging because of their ability to capture structural and textural features for pathology [5][6].

In our work, the term “handcrafted features” refers to features that are explicitly designed based on domain knowledge, rather than learned through training (as in deep learning). Specifically, these features are computed using traditional texture descriptors, such as statistical measures derived from gray-level co-occurrence matrices (GLCM), local binary patterns (LBP), or other classical texture analysis techniques. These descriptors are extracted directly from the image data before any processing by the neural network.

However, previous approaches have primarily relied on either deep learning or handcrafted descriptors, often neglecting the potential advantages of combining both approaches to enhance the feature representation and classification performance.

To address this gap, we propose an efficient deep-learning-based approach for CRC histopathological analysis, integrating a lightweight Convolutional Neural Network (CNN) with handcrafted texture features. Our method significantly reduces the computational complexity while maintaining high classification performance. Additionally, our approach improves generalization across diverse staining variations, overcoming the main challenges in automated CRC diagnosis.

Our main contributions are as follows: (i) development of a lightweight CNN for CRC classification, (ii) integration of handcrafted and learned features, and (iii) experimental validation demonstrating superior performance compared to state-of-the-art methods.

In a previous study, we evaluated widely adopted lightweight CNN architectures, including MobileNet, SqueezeNet, and EfficientNet [7]. The results obtained guided the architectural choices for the custom lightweight CNN proposed in this study.

The remainder of this paper is organized as follows. Section 2 reviews previous studies on CRC classification. Section 3 details the material and the proposed method. Section 4 discusses the results and Section 5 presents the conclusions.

2. Related Work

Ribeiro et al. [8] proposed a method that integrates multi-dimensional fractal techniques and Haralick descriptors for the classification CRC. This approach incorporates feature selection and conventional classifiers, such as decision tree, random forest, and polynomial methods. Nanni et al. [9] proposed an ensemble of CNNs and descriptors by leveraging both the learned and handcrafted features. They trained separate classifiers for each descriptor, fusing their outputs using a sum rule strategy.

Alinsaif & Lang [10] compared deep feature extraction with Support Vector Machine (SVM) classifiers and fine-tuned CNNs. Paladini et al. [11] proposed different ensembles of CNNs that combined predictions and deep feature fusion to improve the classification performance of Coordinated Cluster Representation (CCR).

Arthi et al. [12] evaluated various CNN architectures trained through Federated Learning (FL), leveraging distributed training to improve model performance without centralized data processing. Kumar et al. [13] developed the CRCCN-Net, a lightweight CNN architecture for CRC classification.

Sharkas & Attallah [14] proposed the Color-CADx system for CRC classification using three CNNs: ResNet, DenseNet, and AlexNet. The method integrates spatial and spectral information via Discrete Cosine Transform (DCT) and Analysis of Variance (ANOVA) for feature selection and dimensionality reduction. Elshamy et al. [15] introduced SADagrad, an improved version of the Adagrad optimizer designed to address its shortcomings in learning rate adjustments during CNN training.

Rodrigues Moreira et al. [16] proposed an AI-as-a-Service (AIaaS) architecture that manages AI models and seamlessly delivers cognitive services to heterogeneous edge devices by integrating FL to train models collaboratively. Sá Junior & Backes [17] proposed a method for CRC image classification using a texture descriptor based on the weights of a randomized neural network, projecting texture information onto a new space using randomized weights and classification with a radial basis SVM.

Pan et al. [18] introduced an enhanced lightweight convolutional neural network (EL-CNN) that combined features from VGG and MobileNet to balance performance and efficiency incorporating convolutional block attention modules to improve classification stability. Das & Hazra [19] proposed a stacking ensemble utilizing pre-trained ResNet and EfficientNet models as weak learners, integrated with an artificial neural network layer acting as a meta-learner.

Table 1. Comparison with Related Work.

Work	Method	Feature	Lightweight
[8]	Texture Descriptors	Handcrafted	○
[9]	Ensemble of CNNs	Hybrid	○
[10]	CNNs	Learned	○
[11]	Ensemble of CNNs	Learned	○
[12]	FL with CNNs	Learned	○
[13]	CRCCN-Net	Learned	●
[14]	CNNs + DCT + ANOVA	Hybrid	●
[15]	SADagrad with CNN	Learned	●
[16]	AIaaS with FL	Learned	●
[17]	Texture Descriptor	Hybrid	●
[18]	EL-CNN	Learned	●
[19]	Ensemble of CNNs	Learned	○
Ours	Ensemble of features	Hybrid	●

In contrast to the aforementioned studies, our proposed approach incorporates handcrafted and learned features within a

lightweight CNN, addressing both performance and efficiency concerns. As outlined in Table 1, previous studies often relied solely on learned or handcrafted descriptors. Our integration leveraged the complementary strengths of both feature types.

3. Material and Methods

3.1 Image Dataset

We used the dataset proposed by [20], which comprises 5,000 histological images of human CRC tissue distributed across eight tissue types (625 images per class). These categories comprise: (1) tumor epithelium, (2) simple stroma, (3) complex stroma, (4) lympho (including immune cell clusters and submucosal lymphoid follicles), (5) debris (including necrosis, hemorrhage, and mucus), (6) normal mucosal gland, (7) adipose tissue, and (8) empty (no tissue). An example of each tissue class is shown in Fig. 1.

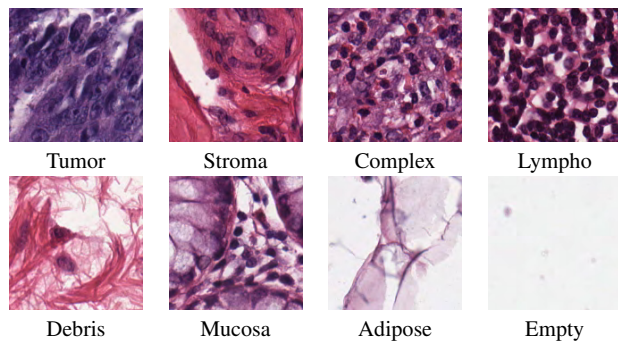


Figure 1. Sample images from Kather dataset [20].

3.2 Texture Descriptors

In computer vision, texture refers to the spatial distribution of intensity or color variations, defining surface properties regardless of shape. Features such as granularity, contrast, regularity, and orientation are extracted using statistical methods [21], frequency-based techniques [22], agent-based approaches [23], and deep learning [24]. In this study, we considered different texture descriptors, each designed to capture complementary visual characteristics from RGB histological images.

- **Chromaticity Moments:** statistical moments (mean, standard deviation, and skewness) computed from the chromaticity components of RGB images, capturing color distribution independently of intensity [25].
- **Gabor Filter FEE:** texture and edge information extracted using Gabor filters, which effectively encode frequency and orientation patterns [22].
- **Haralick LBP:** a fusion of Haralick features and LBP, combining structural and statistical texture information from RGB images [21].
- **Micro-Structure Descriptor (MSD):** captures directional texture patterns across multiple scales, ensuring

robustness to scale and orientation changes in RGB images [26].

- **MultiLayer CCR:** encodes spatial color relationships using co-occurrence matrices across multiple RGB layers, capturing combined color-texture information [27] [28].

In addition, we computed texture features after performing color deconvolution, as described in [29]. This technique separates stains, such as *hematoxylin*, *eosin*, and *diaminobenzidine (DAB; brown)*, by transforming the RGB image into an orthonormal space, allowing independent analysis of each dye.

3.3 Proposed Lightweight Approach

We propose a lightweight ensemble approach that integrates handcrafted texture descriptors with features learned by a compact CNN to improve CRC image classification, as illustrated in Fig. 2.

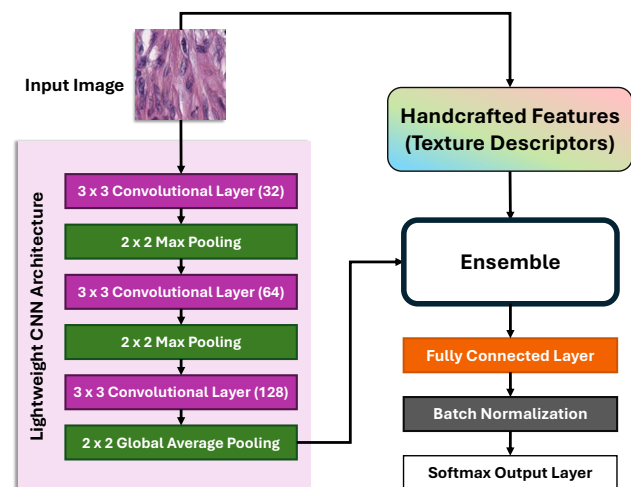


Figure 2. Proposed lightweight CNN and ensemble approach.

We processed the input images through a lightweight CNN composed of three convolutional blocks, each containing a 3×3 convolutional layer, followed by 2×2 max pooling, with increasing filter sizes (32, 64, 128). A global average pooling layer was applied at the end to generate a low-dimensional yet informative feature vector. Simultaneously, handcrafted features are obtained using texture descriptors. We concatenated learned and handcrafted features into a unified vector and passed it through an ensemble module that integrated their complementary information.

The proposed CNN with approximately 160,000 trainable parameters (see Table 2) significantly reduces the computational and memory requirements, making the approach suitable for deployment in resource-constrained clinical scenarios.

Table 2. Layer Details of the proposed lightweight CNN.

Layer	Output Shape	Parameters
Input	(224, 224, 3)	0
Conv2D	(224, 224, 32)	896
MaxPooling2D	(112, 112, 32)	0
Conv2D	(112, 112, 64)	18,496
MaxPooling2D	(56, 56, 64)	0
Conv2D	(56, 56, 128)	73,856
MaxPooling2D	(28, 28, 128)	0
Global Average Pooling	(128)	0
Input (Texture Descriptors)	(10)	0
Global Average Pooling	(128)	0
Fully Connected	(128)	1,408
Ensemble	(256)	0
Fully Connected	(256)	65,792
Batch Normalization	(256)	1,024
Fully Connected (Output)	(8)	2,056
Total Parameters		163,528 (638.78 kB)
Trainable Parameters		163,016 (636.78 kB)
Non-trainable Parameters		512 (2.00 kB)

4. Results and Discussion

We conducted all experiments in a virtual machine with 64 GB of RAM, 32 vCPU, and an NVIDIA Quadro RTX 6000 GPU on the Fabric testbed [30]. The experiments were programmed using Python 3.8.10 and TensorFlow 2.17.0 [31], with CUDA version 12.2, and the operating system Ubuntu 20.04.6 LTS. The dataset was split into 80% for training and 20% for testing, and classification performance was evaluated using four standard metrics: accuracy (acc.), precision (prec.), recall (rec.), and F1-score (F1).

Table 3 presents the results obtained by combining descriptors from a texture method with the proposed network model. For this combination we considered or not the color devolution process before computing the descriptors. Methods that explore color information in combination with the spatial organization of pixels, such as Haralick+LBP and MultiLayer CCR, obtained better results. However, it is important to highlight the results obtained by Chromaticity Moments. This approach analyzes the chromaticity distribution of the images to extract features from the texture pattern. To do so, it does not explore local pixels' patterns, but the color distribution.

Regarding deconvolution, considerable gains are observed in the Haralick+LBP and Chromaticity Moments. On the other hand, this approach substantially affects the performance of the MultiLayer CCR, indicating that this operation is not suitable for all color texture analysis methods.

Despite the good results of this ensemble, what we actually have is a degradation of the result obtained by CNN alone (baseline), as shown in Table 4. Combining learned features with handcrafted features results in a minimum drop of 1.2% in accuracy. This may be an indication that some

Table 3. Results obtained for each texture method combined with the proposed CNN.

Descriptor	Acc. (%)	Prec. (%)	Rec. (%)	F1. (%)
Chrom. Moments	92.80	92.91	92.76	92.77
Chrom. Moments deconv.	93.80	93.81	93.85	93.80
GaborFilter EEE	90.30	90.68	90.22	90.30
GaborFilter EEE deconv.	89.00	89.14	89.15	89.02
Haralick + LBP	92.00	92.05	92.10	91.96
Haralick + LBP deconv.	94.00	94.02	94.06	94.02
MSD	84.10	85.25	84.27	84.28
MSD deconv.	85.50	85.60	85.52	85.49
MultiLayer CCR	94.40	94.40	94.41	94.38
MultiLayer CCR deconv.	91.20	91.26	91.24	91.19
CNN (baseline)	95.60	95.56	95.49	95.50

Table 4. Results obtained by combining the proposed CNN with best texture methods.

Experiment	Acc. (%)	Prec. (%)	Rec. (%)	F1. (%)
CNN (baseline)	95.60	95.56	95.49	95.50
CNN				
+ Haralick LBP deconv.	98.35	98.38	98.37	98.37
+ MultiLayer CCR				
CNN				
+ Haralick LBP deconv.	98.95	98.96	98.94	98.95
+ Chrom. Moments deconv.				
CNN				
+ Chrom. Moments deconv.	98.70	98.69	98.70	98.69
+ MultiLayer CCR				
CNN				
+ Haralick LBP deconv.	99.63	99.63	99.63	99.63
+ MultiLayer CCR				
+ Chrom. Moments deconv.				

texture attributes incorporated into CNN are irrelevant or have some level of redundancy with those learned. Chromaticity Moments are essential for capturing the color distribution, whereas Haralick+LBP focuses on fine local texture patterns that the CNN may have overlooked owing to its coarser filters. Different texture methods explore distinct characteristics of images, such as color distribution and local patterns. Thus, it makes sense to combine and evaluate the features obtained from different sources.

Considering the three best sets of descriptors from Table 3, we applied Principal Component Analysis (PCA) to select the top ten features from each descriptor. PCA was used to reduce the dimensionality of the handcrafted feature vectors while preserving the most informative components, minimizing redundancy and improving the efficiency of the ensemble.

Table 4 presents the results when we combined our CNN with these descriptors. Results show a noticeable increase in the accuracy of the ensemble compared to the baseline (CNN), with all combinations of CNN and texture features exceeding 98%. In addition to high accuracy, the F1 score shows a good balance between precision and recall by the ensemble.

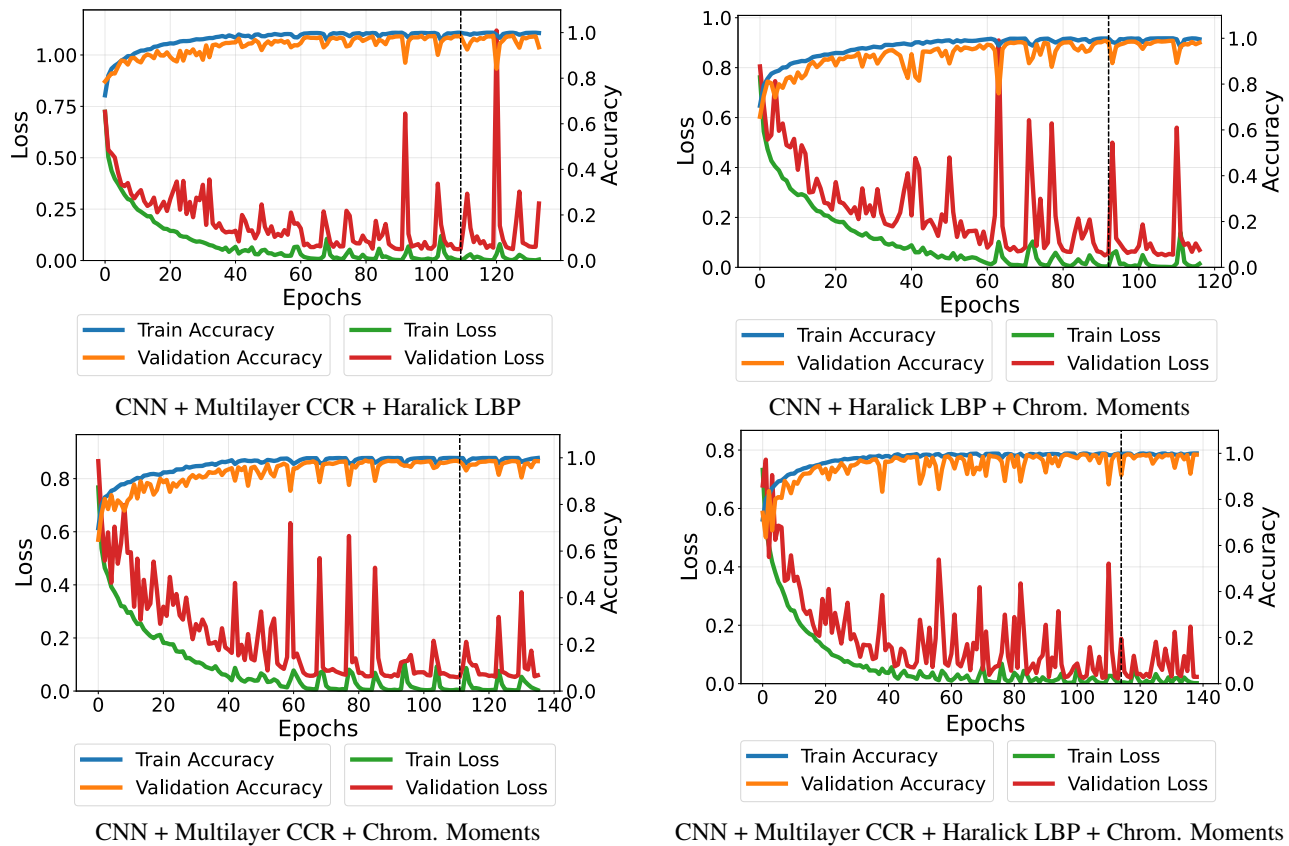


Figure 3. Training curves obtained for the best texture methods combine with proposed CNN.

We obtained the best results when we combined the proposed CNN with the three sets of texture descriptors: Haralick+LBP and Chromaticity Moments, both methods obtained after applying deconvolution to the images, and MultiLayer CCR. Such fusion of features resulted in a very light CNN model, with 1.93 MB size.

Figure 3 illustrates the training and validation behaviors when considering the best feature fusion strategies. As the training progressed, the model refined its ability to extract features, leading to a steady increase in accuracy and a reduction in training loss. We also employed early stopping to prevent overfitting and ensure better generalization. The integration of handcrafted descriptors provides complementary structural and textural information, allowing CNN to enhance its feature representation. These results validate that our approach enables efficient learning while maintaining the generalization capability.

Comparison with the state of the art is an important step in validating a novel approach or method. Table 5 shows the results from recent literature. Although the difference in results between our proposal and the second best result [15] is small (only 1.66%), we must emphasize that our CNN proposal, even when combined with handcrafted attributes, results in a much simpler model. To obtain their result, [15] proposed a new optimizer and evaluated pre-trained models (MobileNet and YOLO) with transfer learning and data augmentation,

resulting in deeper CNNs and with a more complex training process than ours. This comparison shows that our proposal stands out from the results obtained by several other authors over the years, indicating that it is a feasible approach for the CRC classification.

Table 5. Comparison with literature.

Work	Accuracy (%)
Kumar et al. (2023) [13]	93.50
Sá Junior & Backes (2024) [17]	94.36
Pan et al. (2025) [18]	95.24
Alinsaif & Lang (2020) [10]	95.40
Arthi et al. (2022) [12]	96.00
Paladini et al. (2021) [11]	96.16
Rodrigues Moreira et al. (2024) [16]	96.40
Sharkas & Attallah (2024) [14]	96.80
Das & Hazra (2025) [19]	97.20
Nanni et al. (2020) [9]	97.60
Ribeiro et al. (2019) [8]	97.68
Elshamy et al. (2024) [15]	98.00
Our Approach	99.63

5. Conclusion

In this paper, we address the problem of CRC classification from histological images of human tissue using computer vision and deep learning. To accomplish that, we proposed an ensemble of a Lightweight CNN and handcrafted texture features. We obtained the latter from various color texture methods and investigated how different approaches impact the performance of the ensemble. The results show that our approach surpasses state of art methods in terms of accuracy, demonstrating it to be a feasible solution for this classification problem.

In future work, we plan to explore other deep learning models such as MobileNet, SqueezeNet, and EfficientNet. We also intend to evaluate our approach on different medical datasets and hyperparameter optimization, and investigate federated learning as a privacy-preserving strategy for collaborative training across medical institutions without sharing patient data.

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Author Contributions

Larissa Ferreira Rodrigues Moreira contributed to experiments, conception, design, writing, and funding; André R. Backes contributed to supervision, writing, statistical analysis, and funding.

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