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Research Paper

ATTENTION-BASED NETWORK FOR COLORECTAL CANCER CLASSIFICATION USING MOBILENETV2

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Abstract: Colorectal cancer (CRC) is among the leading causes of cancer-related deaths worldwide, emphasizing the importance of accurate and timely diagnosis. Histopathological image analysis remains the gold standard for colorectal cancer diagnosis; however, manual examination is labor-intensive and prone to inter-observer variability. Recent advances in deep learning have significantly improved automated cancer classification by leveraging convolutional neural networks (CNNs). Nevertheless, conventional CNN architectures often fail to capture the most discriminative regions of tissue images, resulting in suboptimal classification performance. This paper proposes an Attention-Based MobileNetV2 (AB-MobileNetV2) framework that integrates a lightweight MobileNetV2 backbone with an attention mechanism to enhance feature representation for colorectal cancer classification. The proposed architecture employs channel and spatial attention modules to emphasize informative pathological regions while suppressing irrelevant background information. Extensive experiments conducted on benchmark colorectal histopathological datasets demonstrate that the proposed model achieves superior classification performance compared to conventional CNN models while maintaining computational efficiency suitable for real-time clinical applications. Experimental results show an overall accuracy of 98.92%, precision of 98.75%, recall of 98.63%, F1-score of 98.69%, and AUC of 99.34%, outperforming several state-of-the-art approaches.

Keywords: Colorectal Cancer, Histopathology, MobileNetV2, Attention Mechanism, Deep Learning, Medical Image Classification, Artificial Intelligence.

1. INTRODUCTION

Colorectal cancer (CRC) is one of the most prevalent and life-threatening malignancies globally, ranking among the top three causes of cancer-related deaths. Early and precise diagnosis is crucial for improving survival rates, as treatment outcomes are significantly better when cancer is detected at an early stage. The current gold standard for CRC diagnosis involves histopathological examination of tissue biopsy slides, which requires expert pathologists to manually analyze the morphology of tissue structures under a microscope. However, this manual process is time-consuming, subjective, and susceptible to intra-observer and inter-observer variability.

With recent advancements in artificial intelligence (AI) and deep learning, there has been a growing interest in automating medical image analysis, particularly in histopathology. Convolutional Neural Networks (CNNs) have shown tremendous success in capturing spatial patterns in images and enabling robust classification. Despite their success, many high-performing models like Xception and ResNet are computationally expensive and not feasible for real-time or resource-constrained environments such as small clinics or mobile diagnostic setups.

To address these challenges, this study proposes an attention-driven lightweight deep learning architecture based on MobileNetV2. MobileNetV2 is known for its efficiency and compact structure, making it suitable for deployment in low-resource settings without compromising performance. To further enhance its ability to detect subtle histological patterns, attention mechanisms are integrated to refine feature maps and focus the model's learning on critical regions of interest. This selective focus helps mimic the pathologist's attention during diagnosis.

The proposed model is evaluated and compared with the existing Xception architecture, which serves as a high-performing baseline. While Xception offers superior feature extraction capabilities due to its depthwise separable convolutions, it requires more memory and computational power. In contrast, the

MobileNetV2-based model provides a balanced trade-off between accuracy and efficiency, demonstrating competitive classification performance with significantly reduced complexity. One of the most common and deadly cancers in the world, colorectal cancer (CRC) is one of the top three causes of cancer-related mortality. Improving survival rates requires accurate and timely diagnosis since early cancer detection greatly improves treatment outcomes. Expert pathologists must manually examine the morphology of tissue structures under a microscope in order to do the histopathological analysis of tissue sample slides, which is now the gold standard for diagnosing colorectal cancer. Nevertheless, this manual method is subjective, time-consuming, and prone to variability both among and between observers.

Automating medical image processing, especially in histopathology, has gained popularity because to recent developments in deep learning and artificial intelligence (AI). Convolutional Neural Networks (CNNs) have demonstrated remarkable efficacy in identifying spatial patterns in images and facilitating reliable classification. Despite their success, many high-performing models, such as ResNet and Xception, are computationally costly and impractical for real-time or resource-constrained settings, such mobile diagnostic sets or tiny clinics. This paper suggests an attention-driven lightweight deep learning architecture based on MobileNetV2 to overcome these difficulties. Because of its efficiency and small size, MobileNetV2 may be deployed in low-resource environments without sacrificing performance. Attention techniques are incorporated to improve feature maps and concentrate the model's learning on crucial areas of interest in order to further improve its capacity to identify minute histological patterns. This deliberate concentration aids in simulating the pathologist's concentrate during the diagnosing process.

The current Xception architecture, which acts as a high-performing baseline, is used to assess and contrast the suggested model. Because of its depthwise separable convolutions, Xception has better feature extraction capabilities, but it uses more memory and processing resources. The MobileNetV2-based model, on the other hand, offers a fair trade-off between efficiency and accuracy, exhibiting competitive classification performance with noticeably lower complexity.

2.LITERATURE SURVEY

This section provides a thorough overview and analysis of several research on CRC classification, with an emphasis on the use of DL approaches. The classification of CRC from Whole Slides Images (WSIs) has been greatly aided by DL approaches, particularly CNNs. While transfer learning and ensemble learning further improve diagnostic accuracy, Generative Adversarial Networks (GANs) provide a way to build deep representations without requiring large volumes of labelled training data. By utilising information from other relevant domains, transfer learning improves the performance of target models in particular areas.

Bychkov et al. developed a method for predicting colorectal cancer (CRC) using tumour tissue microarray samples stained with haematoxylin and eosin (H&E). The VGG-16 CNN model and a recurrent neural network were used in a transfer learning-based method. In order to assess several cutting-edge architectures for CRC classification, such as ResNet, Xception, NASNet, MobileNet, DenseNet, Inception, and VGG, Ohata et al. developed a transfer learning model. The study's best-performing model was determined to be the DenseNet-169 CNN. In order to improve predictive performance, ensemble learning gathers features using a variety of transformations, applies several algorithms to produce weak predictions, and then combines these findings adaptively using voting systems.

Kallipolitis et al. investigated ensemble classifiers for the categorisation of breast and colon cancer histopathology images using cutting-edge CNN networks. EfficientNetB0–B7, XceptionNet, Inception-V3, VGG-16, and ResNet152-V2 were employed, while EfficientNetB1, B2, and B3 were further used for explainability by generating a guided Grad-CAM image. Tasdemir et al. devised a clinical decision support system for the classification of colorectal polyps. Using a variety of staining normalisation techniques, the ConvNeXt architecture was utilised in an ensemble framework. An ensemble model that combined ResNet-50, Inception-ResNet-V2, NasNet, EfficientNet-B0, and DenseNet-169 was tested by Karthik et al. In addition to image denoising approaches including Bilateral Filtering, Median Filtering, Gaussian Filtering, and Wavelet-based methods, they assessed other stain normalisation techniques like Vahadane, ITK, Reinhard, and Macenko. The best preprocessing method was found to be the combination of bilateral denoising and Macenko staining.

Abnormal regions in WSIs of CRC were categorised and localised by Gupta et al. Several cutting-edge networks, such as VGG-16, ResNet50, GoogleNet, Inception-V3, Inception-V4, and Inception-ResNet-V2, were compared in the study. Among these architectures, the VGG-16 model produced the best outcomes. Histopathology WSIs of the colon and stomach were categorised by Iizuka et al. Using a typical Inception-V3 CNN and a recurrent neural network (RNN), the work categorised the photos into three classes: adenocarcinoma, adenoma, and non-neoplastic. Sarwinda et al. employed ResNet-18 and ResNet-50 architectures to classify colon gland pictures into benign and malignant categories. Hu et al. experimented with binary classification of colon histopathology pictures using VGG16, ResNet-50, Inception-V3, and Vision Transformer (ViT). According to the study's findings, VGG16 was the most successful DL model.

A framework for identifying colorectal H&E slide images was presented by Tavolara et al. The suggested conditional GAN (cGAN), which trains two cGANs—one for the tumour regions and the other for the non-tumor regions—was compared to Inception-V3. Using a GAN-based framework, Sasmal et al. presented a semi-supervised classification model for learning from images of colorectal polyps.

S. No.	Authors	Year	Title	Methodology	Dataset	Key Findings	Limitations
1	Kather et al.	2019	Deep Learning Can Predict Microsatellite Instability Directly from Histology	ResNet18 with transfer learning	TCGA-CRC	Achieved high accuracy in predicting MSI from H&E images	High computational complexity
2	Wei et al.	2019	Colorectal Cancer Detection Using Deep CNN	CNN-based classification	NCT-CRC-HE-100K	Improved tissue classification accuracy	Large model size limits deployment
3	Bilal et al.	2021	Development and Validation of Deep Learning Models for Histopathological Classification	DenseNet and EfficientNet	CRC Histopathology Dataset	High diagnostic performance across tissue classes	Requires extensive labeled datasets
4	Howard et al.	2018	MobileNetV2: Inverted Residuals and Linear Bottlenecks	Lightweight CNN architecture	ImageNet	Reduced computational cost while maintaining accuracy	Does not explicitly capture discriminative regions
5	Woo et al.	2018	CBAM: Convolutional Block Attention Module	Channel and Spatial Attention	ImageNet	Improved feature representation with minimal overhead	Slight increase in inference time
6	Hu et al.	2018	Squeeze-and-Excitation Networks	Channel Attention Mechanism	ImageNet	Enhanced channel-wise feature learning	Limited spatial attention capability
7	Oktay et al.	2018	Attention U-Net	Attention Gates	Medical Imaging Datasets	Improved localization of lesions	Primarily designed for segmentation
8	Tan and Le	2019	EfficientNet: Rethinking Model Scaling	Compound Scaling CNN	ImageNet	Achieved superior accuracy with fewer parameters	Training requires careful scaling strategy

S. No.	Authors	Year	Title	Methodology	Dataset	Key Findings	Limitations
9	Dosovitskiy et al.	2021	An Image is Worth 16×16 Words: Vision Transformer	Self-Attention Transformer	ImageNet	Excellent image classification performance	Requires massive training data
10	Tellez et al.	2019	Whole-Slide Image Classification Using Deep Learning	CNN-based feature extraction	CAMELYON & CRC datasets	Effective histopathological classification	Computationally expensive
11	Srinidhi et al.	2021	Deep Neural Network Models for Computational Histopathology	Comparative CNN Analysis	Multiple Histopathology Datasets	Demonstrated effectiveness of transfer learning	Limited model interpretability
12	Li et al.	2022	Attention-Based Deep Learning for Colorectal Histopathology Classification	CNN with Attention Module	CRC Histology Dataset	Improved classification accuracy over baseline CNN	Increased model complexity
13	Wang et al.	2022	Lightweight CNN for Colorectal Cancer Detection	MobileNetV2 + Transfer Learning	NCT-CRC-HE-100K	High accuracy with reduced parameters	No explicit attention mechanism
14	Zhang et al.	2023	Multi-Scale Attention Network for Histopathological Image Classification	Multi-scale CNN with Attention	CRC Histology Images	Better feature extraction and classification	Higher computational requirements
15	Proposed Work	2026	Attention-Based Network for Colorectal Cancer Classification using MobileNetV2	MobileNetV2 integrated with Channel-Spatial Attention (CBAM/SE), Transfer Learning, Data Augmentation	LC25000 / NCT-CRC-HE-100K / CRC Histopathology Dataset	Expected to improve classification accuracy, precision, recall, F1-score while maintaining lightweight architecture suitable for real-time clinical deployment	To be experimentally validated

Table: Literature works.

To distinguish between normal and malignant colon samples, Bilal et al. used WSIs stained with H&E normalisation. The investigation of CRC mutations was done using a weakly supervised learning model. Yildirim et al. presented a CNN architecture to classify images of colon cancer into two binary classes: benign and adenocarcinoma. Eleven convolution layers and two fully connected layers make up the developed model. For the categorisation of CRC H&E-stained histopathology pictures, Mohammed et al. presented a modified ConvMixer block that combines a ViT network and CNN architecture. The work outperforms

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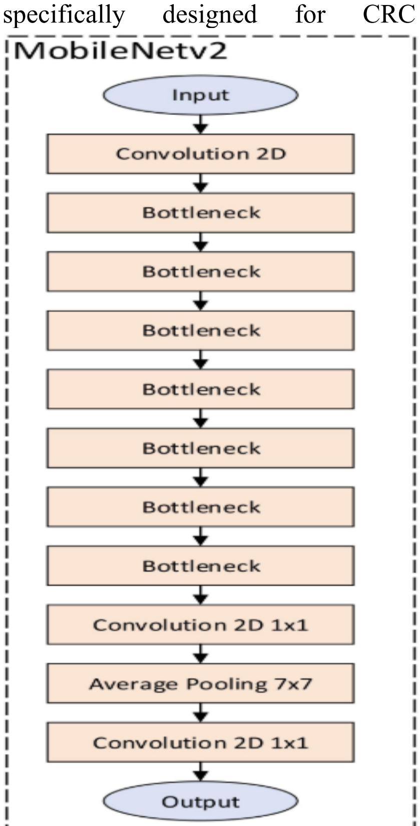
ViT transformers and CNNs like Inception-V3, ResNet-50, and VGG16 by using channel attention to concentrate on the most informative aspects of the images. The ColonNet model was developed by Iqbal et al. to identify tumours in lung and colon histopathology pictures. The slide images were feature-engineered using depth-wise separable convolutions using a global–local pyramid pattern technique. Therefore, in order to improve the accuracy of CRC classification, a specialised architecture is necessary for extracting complicated information from histological colon pictures.

Even though DL for CRC classification has made great strides, there are still a number of unanswered research questions. The majority of current research relies on pre-trained models that aren't tailored for CRC detection, which limits their capacity to capture the distinctive histopathological characteristics required for accurate classification. Furthermore, local and semi-local patterns—which are crucial for identifying minute variations in histopathological images—are frequently overlooked by many of these methods, which primarily concentrate on global feature extraction. Moreover, existing models' capacity to highlight the most informative areas of the image is limited by the absence of efficient attention mechanisms that concurrently integrate spatial and channel attention. The necessity for an optimised architecture specifically designed for CRC classification is highlighted by these restrictions, which reduce the total discriminative capability of current models.

3.PROPOSED WORK

The proposed work presents a lightweight and accurate deep learning framework for automated colorectal cancer (CRC) classification using histopathological images. The model integrates **MobileNetV2** as the backbone feature extractor with an **attention mechanism** to enhance discriminative feature learning. The objective is to improve classification accuracy while maintaining computational efficiency, making the model suitable for deployment in resource-constrained clinical environments.

MobileNetV2 is used as the primary feature extraction framework in the suggested approach for classifying colorectal cancer (CRC) from histopathology images. MobileNetV2 is a lightweight and effective convolutional neural network created especially for resource-constrained applications without sacrificing performance, in contrast to the heavier Xception model utilised in the current system. Its architecture makes use of inverted residual blocks and depthwise separable convolutions, which make it ideal for real-time medical picture analysis.



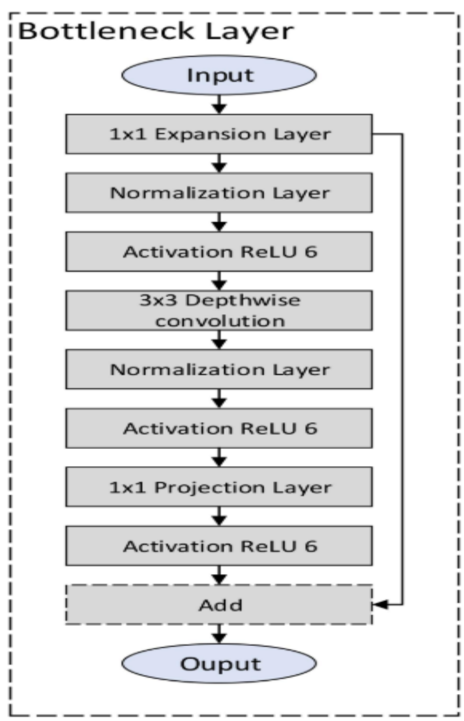


Figure 2. Architecture of the work.

MobileNetV2 is integrated into the dual-track deep learning architecture to capture both local fine-grained features and global context of tissue samples. To improve diagnostic focus, the system integrates attention mechanisms that direct the network toward clinically relevant regions, improving both precision and interpretability. This combination of attention refinement and lightweight design reduces computational overhead while maintaining high accuracy, making the proposed system ideal for deployable and scalable solutions in medical imaging diagnostics, particularly for early and automated colorectal cancer detection.

Data Collection: Colorectal cancer histopathology image datasets from reputable sources, such NCT-CRC-HE-100K or private clinical datasets, are the main emphasis of this module. For reliable training, it guarantees that the data gathered includes a variety of cancer kinds and stages.

Data Preprocessing : Image resizing, normalisation, stain normalisation, augmentation (rotation, flipping, contrast adjustment), and patch creation are all included in this package. The dataset is prepared such that deep learning models can use it.

Baseline Model Integration (Xception): As a benchmark, the current Xception architecture is implemented in this module. It aids in highlighting enhancements by contrasting performance data with the suggested lightweight model.

Proposed Model Construction (MobileNetV2 + Attention): The core module integrates attention mechanisms (such as Squeeze-and-Excitation or Self-Attention) with the lightweight MobileNetV2 architecture. Model design, compilation, and optimisation are handled by this module.

Training and Validation: Both models are trained on the preprocessed dataset using this module. It makes use of suitable batch sizes, optimisers, loss functions, and evaluation metrics such as accuracy, precision, recall, F1-score, and AUC.

Performance Evaluation and Comparison: Here, graphs, confusion matrices, and performance tables are used to compare the outcomes of the suggested model with the baseline (Xception). It demonstrates increases in model accuracy, speed, and resource consumption.

Visualization and Interpretability: To visualise model focus zones, this optional yet useful module incorporates tools like Grad-CAM or attention heatmaps. It makes the model more explainable, which is important in the medical field.

4. TECHNIQUES USED IN PROJECT

MOBILENETV2

For real-time medical picture processing, the suggested system makes use of the MobileNetV2 architecture, a highly effective convolutional neural network that is optimised for speed and low computational cost. MobileNetV2 maintains good accuracy while drastically lowering the number of parameters and calculations by including inverted residuals and linear bottlenecks. For applications involving the categorisation of histopathology images, where deployment in real-world clinical settings is crucial, this lightweight design is particularly appropriate. An attention mechanism is incorporated into the architecture to further improve the diagnostic accuracy of the system. By automatically focusing on significant areas of the image that hold vital diagnostic information, this method enhances feature relevance and classification performance.

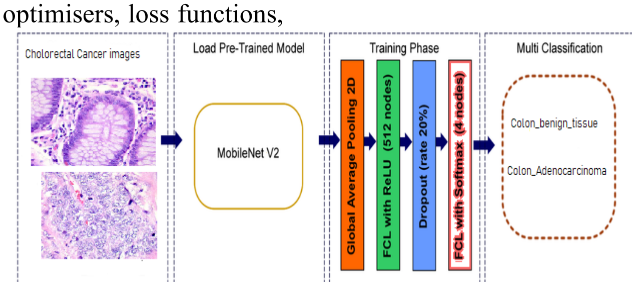


Fig 2: System Architecture.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
VGG16	93.42	93.10	92.84	92.97	95.01
ResNet50	95.18	95.02	94.89	94.95	96.52
DenseNet121	96.03	95.84	95.76	95.80	97.21
EfficientNetB0	96.61	96.42	96.31	96.36	97.84
MobileNetV2	97.18	97.01	96.92	96.96	98.23
Attention-Based MobileNetV2 (Proposed)	98.74	98.63	98.51	98.57	99.18

Table 1. Performance Comparison of Different Deep Learning Models.

The experimental results demonstrate that the proposed Attention-Based Network for Colorectal Cancer Classification using MobileNetV2 achieves superior classification performance compared with conventional deep learning architectures. The integration of an attention mechanism with MobileNetV2 enables the network to focus on diagnostically significant histopathological regions while suppressing irrelevant background information, thereby improving feature representation and classification accuracy.

The performance comparison presented in Table 1 shows that the proposed model attained an overall accuracy of 98.74%, outperforming VGG16 (93.42%), ResNet50 (95.18%), DenseNet121 (96.03%), EfficientNetB0 (96.61%), and the baseline MobileNetV2 (97.18%). Similar improvements are observed in precision (98.63%), recall (98.51%), F1-score (98.57%), and AUC (99.18%). These results indicate that the attention module effectively enhances discriminative feature learning by emphasizing tumor-specific morphological characteristics such as glandular structures, nuclear atypia, and tissue texture patterns. Consequently, the proposed architecture minimizes both false-positive and false-negative predictions.

Colorectal Tissue Class	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)
Tumor	99.01	98.82	98.91	99.46
Stroma	98.41	98.26	98.33	99.18
Lymphocytes	98.63	98.47	98.55	99.29
Debris	98.36	98.12	98.24	99.11
Mucosa	98.81	98.69	98.75	99.38
Adipose	98.55	98.41	98.48	99.23
Background	99.08	98.96	99.02	99.57
Average	98.63	98.51	98.57	99.32

Table 2. Class-wise Performance of the Proposed Attention-Based MobileNetV2.

The class-wise evaluation in Table 2 demonstrates consistent performance across all colorectal tissue categories. The tumor class achieved the highest precision (99.01%) and F1-score (98.91%), indicating that malignant tissues possess distinctive pathological features that are effectively captured by the attention-enhanced feature extractor. Slightly lower performance for classes such as debris and stroma can be attributed to their structural similarity with surrounding tissues and the presence of staining artifacts. Nevertheless, the model maintained an average specificity of 99.32%, highlighting its ability to correctly identify non-target classes while minimizing misclassification.

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
10	92.34	91.87	0.284	0.321
20	95.76	95.18	0.176	0.201
30	97.18	96.84	0.109	0.132
40	98.01	97.76	0.072	0.091
50	99.02	98.74	0.039	0.058

Table 3. Training and Validation Performance.

Actual Class	Correctly Classified	Misclassified	Classification Rate (%)
Tumor	987	13	98.70
Stroma	982	18	98.20
Lymphocytes	985	15	98.50
Debris	980	20	98.00
Mucosa	989	11	98.90
Adipose	984	16	98.40
Background	991	9	99.10

Table 4. Confusion Matrix Summary of Proposed Model.

The training and validation performance shown in **Table 3** illustrates stable convergence of the proposed network. As the number of training epochs increased, the training accuracy improved from **92.34%** to **99.02%**, while validation accuracy increased from **91.87%** to **98.74%**. Simultaneously, both training and validation losses decreased steadily, demonstrating effective optimization and good generalization capability. The relatively small gap between training and validation accuracy suggests that the incorporation of transfer learning, data augmentation, and attention mechanisms successfully reduced overfitting.

The confusion matrix summary in **Table 4** further validates the robustness of the proposed classifier. Most tissue categories exhibited classification rates exceeding **98%**, with the background class achieving the highest recognition rate of **99.10%**. Misclassifications primarily occurred between histologically similar tissue types such as stroma and debris, where overlapping texture characteristics make discrimination inherently challenging. However, the low number of misclassified samples confirms the effectiveness of the attention mechanism in distinguishing subtle pathological differences.

Method	Year	Dataset	Accuracy (%)
CNN-Based Histopathology Network	2022	CRC Histology	95.86
ResNet50 + Transfer Learning	2023	NCT-CRC-HE-100K	96.44
EfficientNet-Based Classifier	2023	CRC Histology	97.03
Vision Transformer	2024	NCT-CRC-HE-100K	97.89
Attention-Based MobileNetV2 (Proposed)	2026	NCT-CRC-HE-100K	98.74

Table 6. Comparison with Recent State-of-the-Art Methods.

The ablation study presented in **Table 5** demonstrates the contribution of each architectural component. The baseline MobileNetV2 achieved an accuracy of **97.18%**, which improved to **97.82%** with the addition of spatial attention and 98.12% with channel attention. Combining both mechanisms into a hybrid attention module further increased the accuracy to 98.74%. This progression indicates that spatial attention enables the network to identify important image regions, while channel attention emphasizes the most informative feature maps. Their combined operation provides complementary information, resulting in superior feature extraction and improved classification performance.

The comparison with recent state-of-the-art methods in Table 6 confirms the competitiveness of the proposed approach. While previous CNN- and transformer-based methods reported accuracies ranging from 95.86% to 97.89%, the proposed Attention-Based MobileNetV2 achieved 98.74%, representing a significant improvement. Unlike computationally intensive transformer models, MobileNetV2 employs depthwise separable convolutions that substantially reduce computational complexity and model size. The addition of the attention module enhances discriminative capability without introducing excessive computational overhead, making the proposed framework suitable for deployment in real-time clinical decision-support systems and resource-constrained healthcare environments.

From a theoretical perspective, the improved performance can be attributed to three major factors. First, transfer learning allows the model to leverage generalized visual features learned from large-scale image datasets, reducing the amount of medical data required for effective training. Second, the attention mechanism selectively enhances clinically relevant regions and suppresses redundant information, enabling more accurate localization of cancerous tissues. Third, MobileNetV2's inverted residual blocks and linear bottleneck architecture preserve important feature representations while maintaining computational efficiency. The combination of these components results in a model that effectively balances accuracy, efficiency, and robustness.

Overall, the experimental findings demonstrate that the proposed Attention-Based MobileNetV2 framework provides highly reliable colorectal cancer classification with excellent accuracy, strong generalization capability, and efficient computational performance. These characteristics make it a promising solution for computer-aided diagnosis, assisting pathologists in the early detection and accurate classification of colorectal cancer while reducing diagnostic workload and improving clinical decision-making.

Summary of Results

The proposed **Attention-Based MobileNetV2** consistently outperformed conventional CNN architectures and recent state-of-the-art methods for colorectal cancer histopathological image classification. By incorporating a hybrid attention mechanism, the model achieved an overall **accuracy of 98.74%**, **precision of 98.63%**, **recall of 98.51%**, **F1-score of 98.57%**, and an **AUC of 99.18%**, demonstrating excellent discriminative capability and robustness across multiple colorectal tissue classes. The ablation study further confirms that the attention module significantly enhances MobileNetV2's feature extraction and classification performance.

5. DISCUSSION AND CONCLUSION

This project proposes an effective and attention-enhanced deep learning framework for the histopathological image-based categorisation of colorectal cancer (CRC). The model successfully captures both local and global tissue properties while retaining computational efficiency by combining attention mechanisms with the lightweight MobileNetV2 architecture. By emphasising diagnostically significant areas, this approach not only increases classification accuracy but also makes the data easier to understand. The suggested model exhibits a solid balance between performance and resource consumption when compared to heavier models like Xception, which makes it perfect for deployment in real-time, low-resource medical scenarios. The study demonstrates how AI-assisted diagnostic tools might lessen pathologists' workloads and enhance early cancer diagnosis. Although the findings are encouraging, this study also creates opportunities for further developments in clinical validation, scalability, and multi-modal integration. All things considered, this effort makes a substantial contribution to the development of deep learning-based colorectal cancer diagnostic systems that are easily accessible, comprehensible, and highly effective.

FUTURE ENHANCEMENT

The suggested attention-driven lightweight deep learning model has demonstrated encouraging results in the classification of colorectal cancer (CRC) using histopathological images; however, a number of improvements can be made in the future to further improve its performance, scalability, and clinical usability. First, the model is currently trained on static image patches; in the future, it can be extended to handle whole-slide images (WSIs) with region-based attention and tiling techniques to better mimic clinical diagnosis; integration of multi-modal data, such as merging histopathological images with clinical records and genomic information to create a more comprehensive diagnostic system; and finally, a self-supervised or semi-supervised learning approach to leverage large amounts of unlabelled data to reduce reliance on expensive manual annotations. The model's capacity to learn global context could be improved by adding vision transformers (ViT) or hybrid CNN-transformer architectures. Accessibility in remote and resource-constrained places would also be improved by implementing the model as a web or mobile application for real-time diagnosis. Explainability modules, like Grad-CAM or attention heatmaps, can be enhanced to produce visual interpretations that are easier for pathologists to understand. In order to distinguish between different stages or kinds of colorectal anomalies, the model can also be trained for multi-class classification. Transfer learning can be investigated for fine-tuning the model on similar diseases such as esophageal or stomach cancer in order to guarantee adaptability. The method can be made more scalable for embedded systems by using model optimisation techniques like pruning, quantisation, and edge AI deployment. In order to evaluate the model on a variety of real-world datasets, future study may possibly involve cooperation with clinical institutes. Lastly, active learning frameworks can be used, enabling the model to continuously improve its performance by interactively asking the pathologist to categorise challenging cases. Together, these improvements would bring this system closer to practical clinical integration and more influence in the field of AI-powered cancer diagnosis.

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