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Original Article

A Context-Adaptive Dual Cross-Attention Fusion Framework with Incremental Learning for Robust Lung and Colon Histopathology Classification

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Abstract *- The accurate recognition of lung and colon histopathological images is still one of the most difficult tasks within computational pathology, mainly due to the morphological similarities of different malignancies. This study proposes a novel Context Adaptive Dual Cross Attention Feature Fusion with Incremental Learning framework for efficient multi-class histopathology image classification on the LC25000 dataset. Specifically, the authors' model combines deep spatial features from the VGG13 architecture with multiple handcrafted domain features, such as colour histograms, Local Binary Patterns (LBPs), and Grey-Level Co-Occurrence Matrices (GLCMs), using a token-based cross-attention module. To stabilise attention learning by considering the impact of tissue morphology on affinities, the authors propose a context-adaptive bias modulation strategy. Moreover, a token importance reweighting method is considered to increase the contribution of discriminative features. To address the problem of catastrophic forgetting in multi-class histopathological classification, the incremental learning method is applied. Experimentally, the authors' method achieved an accuracy of 0.9869, an F1-macro score of 0.9862, an AUC-macro score of 0.9924, and a Cohen's kappa of 0.9838. The proposed solution outperformed all baseline feature fusion approaches considered. In particular, the model demonstrated promising results for the lung subtype classification task.*

Keywords *- Histopathology image classification, dual Cross-Attention fusion, Context-Adaptive bias modulation, Handcrafted-Deep feature fusion, Incremental learning.*

1. Introduction

Apart from other forms, cancers of the lungs and colon are among the top two cancers that lead to death caused by cancer in the world, necessitating early detection of these diseases. Microscopic examination of the cells following hematoxylin and eosin staining has been known to be the best means for the diagnosis of cancer due to its ability to provide detailed information about cell morphology and structure. The method is, however, not only time-consuming but also observer-dependent and plagued by inconsistency in diagnoses of similar cancers, such as lung adenocarcinoma and squamous cell carcinoma. The invention of artificial intelligence, specifically machine learning techniques, has transformed histopathology because of its ability to help in the automation of image analysis. Convolutional Neural Networks and transformer models have shown great utility in cancer diagnosis based on their ability to learn complicated patterns. However, issues like inconsistent staining, similarity of classes, lack of generalisation, and computational complexity make the use of these models impractical in medicine. Recent research trends have extensively focused on developing better ways of classifying cancer from histopathological samples using deep learning approaches. The multichannel dense architecture, introduced in 2024, improved cancer classification for lung and colon cancers on the basis of LC25000 and NCT-CRC-HE-100K datasets, making clear the importance of multiple data modalities [1]. Similarly, a hybrid CNN architecture, based on MobileNet and Xception architectures, has been used for improving the classification results through feature-level hybridisation [2]. Some significant developments in terms of architecture optimisation and hybrid learning have also been made in 2024. Automated deep learning approaches have further improved histopathological classification performance through optimized convolutional architectures [3]. The texture-based manually extracted feature techniques, like Local Binary Pattern (LBP), have also shown good discriminative power for the histopathology image classification task [4]. Hybrid

approaches based on deep learning have been used to improve classification accuracy using multiple representations of the same features [5].

1.1. Literature Review

Recent advances (2025-2026) involve the development of compact and applicable models. Lightweight CNN designs were introduced that have lower computational requirements yet retain high accuracy, making them candidates for implementation in real time [6]. Multi-scale feature integration through deep learning features, along with a feature selection technique, has been proven effective for improving classification accuracy with high efficiency [7]. Additionally, Explainable AI (XAI) approaches were used to incorporate transparency and reliability into machine learning models in the context of medical diagnostics. The use of hybrid preprocessing techniques that use Gaussian filters in addition to deep learning is one way to enhance features and visualisation for diagnostic purposes [8], and Hybrid convolution and EfficientNet frameworks have recently been explored for lung and colon histopathology images [9, 10]. Lately, the Vision Transformer (ViT) architecture has proved its capability of capturing long-term spatial dependency in histopathological images, which enhances the classification of lung and colon cancer tissue [12]. Another important aspect is that by combining hand-crafted texture descriptors with deep convolutional features, there is additional complementary pathology information that enhances the robustness and classification of lung and colon histopathological images [13].

Classification of the histopathology images of lungs and colons poses unique problems, considering the similarity of cancer and normal tissues in terms of texture, cell organisation, staining pattern, and glandularity. It becomes much more difficult when classifying the cancers of a certain type, since there are very few inter-class differences but significant intra-class differences. While deep learning algorithms perform rather well in such tasks, they still cannot reliably recognise clinically significant patterns within the samples. Thus, the development of a classification system able to detect both global semantic and local pathological patterns is needed. Despite the substantial advances attained by convolutional neural networks, transformer architectures, and deep learning fusion methods for histopathological image classification, some significant challenges persist.

Firstly, the vast majority of the proposed solutions rely on the use of deep features obtained from either CNNs or transformers and neglect the incorporation of handcrafted pathological features, encoding such properties of the tissue structures as colours, textures and morphology.

Secondly, even though attention mechanisms for feature fusion have become quite popular, many state-of-the-art models use static and one-way attention, failing to adapt the way feature interactions occur depending on the contextual information about particular tissue and, therefore, resulting in inefficient discrimination of morphologically similar classes such as lung adenocarcinoma and lung squamous cell carcinoma.

Thirdly, almost all available frameworks conduct feature aggregation after performing global pooling, which may lead to loss of essential local histological patterns needed for the classification of the fine-grained cancer subtypes.

Lastly, almost all research works are dedicated to the improvement of classification accuracy of histopathology images, but ignore the task of sustaining performance with the change in the distribution of the training data, which makes these frameworks susceptible to catastrophic forgetting and a lack of generalisation capabilities. The suggested work will be implemented with the open LC25000 dataset that includes 25,000 images divided into five categories: benign colon tissue, benign lung tissue, colon adenocarcinoma, lung adenocarcinoma, and lung squamous cell carcinoma. Each image is in RGB form and sized at 224x224 pixels, suitable for CNNs. The dataset will be divided in a stratified manner without any personal information in order to avoid any ethical issues associated with privacy protection and data usage.

Table 1. Comparative analysis of existing histopathology classification approaches and the proposed framework

Ref.	Methodology	Deep Features	Handcrafted Features	Attention Fusion	Context Adaptive	Incremental Learning
[1]	Multi-modal Dense Architecture	✓	✗	✗	✗	✗
[2]	MobileNet–Xception Hybrid CNN	✓	✗	✗	✗	✗
[3]	Automated CNN-based Histopathology Classification	✓	✗	✗	✗	✗
[6]	Lightweight Explainable CNN	✓	✗	✗	✗	✗
[7]	Multi-scale Deep Feature Integration	✓	✗	✗	✗	✗

[12]	Vision Transformer (ViT)-based Classification	✓	✗	✓	✗	✗
[13]	Heterogeneous CNN + Handcrafted Feature Fusion	✓	✓	✗	✗	✗
Proposed	Context-Adaptive Dual Cross-Attention Framework	✓	✓	✓	✓	✓

As seen from Table 1, the previous approaches are able to handle only some of the problems of the histopathology classification process; however, the proposed framework takes care of deep feature fusion, context-aware attention, and incremental learning in one model. The research gaps described above motivate the need for a novel architecture named Context-Adaptive Dual Cross-Attention Fusion Framework with Incremental Learning, which aims at robust classification of multi-class histopathological images. The architecture proposed in this study combines deep spatial information obtained from the VGG13 backbone network with handcrafted feature descriptors based on the histogram of RGB intensities, Local Binary Pattern (LBP), and Grey Level Co-occurrence Matrix (GLCM). Contrary to traditional late fusion schemes, the proposed architecture implements token-wise feature fusion using a cross-attention mechanism that allows for interactions between handcrafted features and deep learned features in a bidirectional manner.

To further enhance the feature discrimination in morphologically similar classes, a context-adaptive bias modulation layer is implemented to dynamically adjust the attention weights in accordance with overall tissue properties. A token importance reweighting technique is employed to emphasise clinically useful tokens, while an incremental learning scheme is adopted to minimise the catastrophic forgetting effect. The performance of the proposed framework is verified by using the LC25000 dataset involving five classes of lung and colon tissues.

This proposed methodology presents several innovative methodological aspects compared to state-of-the-art histopathology image classification methods. First, in contrast to traditional deep learning models based only on deep convolutional or transformer networks, the proposed framework includes complementary pathological descriptors, such as RGB histogram, LBP, and GLCM, together with deep spatial descriptors provided by a VGG13 backbone network. Second, bidirectional cross-attention fusion is suggested to enable the exchange of information between handcrafted and deep feature spaces at the token level to preserve discriminative local tissue characteristics ignored in the conventional late fusion approach. Third, the context-adaptive bias modulation is suggested to modulate attention interactions in accordance with global tissue morphology to achieve better discrimination between morphologically similar cancer subtypes. Fourth, the reweighting of tokens to focus attention only on discriminative representations is included in the model. Fifth, an incremental learning methodology is applied to avoid catastrophic forgetting. All these innovations create a unified approach that takes into account feature complementation, adaptive attention learning, discriminative representation improvement, and knowledge persistence.

2. Materials and Methodology

2.1. Proposed Framework Overview

This novel model is designed as a dual stream model with context-aware bidirectional attention for multi-class histopathology classification. The overall structure consists of three main stages as depicted in Figure 1. These are (i) data pre-processing and dual stream-based feature extraction, (ii) token-level fusion through context-aware bidirectional attention, and (iii) classification through a compact neural decision head. Unlike classical single-stream convolution models, the proposed model uses both handcrafted and deep representation features at the token level before aggregation. In doing so, the proposed framework will maintain the discriminative local features that would otherwise be neglected by traditional late fusion systems. The architectural changes induced by the novel idea are depicted in Figure 2.

2.2. Data Preprocessing and Input Representation

The histopathology data from LC25000 is employed, comprising five equal classes of benign and malignant tissue of lung and colon types [11]. The dimensions of all images are uniformly reduced to 224 x 224 pixels and standardized to maintain constant input statistics for each image. Stratified splitting is used with an 80%:20% ratio for training and testing samples while employing horizontal and vertical flipping only on the training samples.

2.3. Deep Spatial Feature Extraction using VGG13

As compared to the baseline EfficientNet architecture, the proposed method uses a VGG13-based convolutional network pre-trained on the ImageNet dataset. The use of VGG13 is justified by its simple architecture, stable representation, and enhanced explainability for medical images. Given an image I, the VGG13 encoder yields the feature map,

$$F_{tnn} = \phi_v^{aW13}(I) \quad (1)$$

which is further flattened to form a sequence of spatial tokens $T_s \in \mathbb{R}^{\wedge}(N \times d)$. Each token represents localized features of the image, such as gland structure, nucleus distribution, and texture.

2.4. Multi-Domain Handcrafted Feature Tokenisation

In addition to deep feature improvement, the system makes use of handcrafted features from different domains. Three handcrafted feature types are generated, namely, (i) RGB histogram for colour distribution, (ii) Local Binary Pattern (LBP) for microtexture, and (iii) Grey-Level Co-occurrence Matrix (GLCM) for texture relationship features. This results in the production of one handcrafted feature vector:

$$T_h = \{H^{BGB}, F^{LB}P, F^{GL}HO\} \quad (2)$$

Each of the features plays an important role in the appearance of tissues. Multi-domain handcrafted features improve the robustness against stains and morphological similarities.

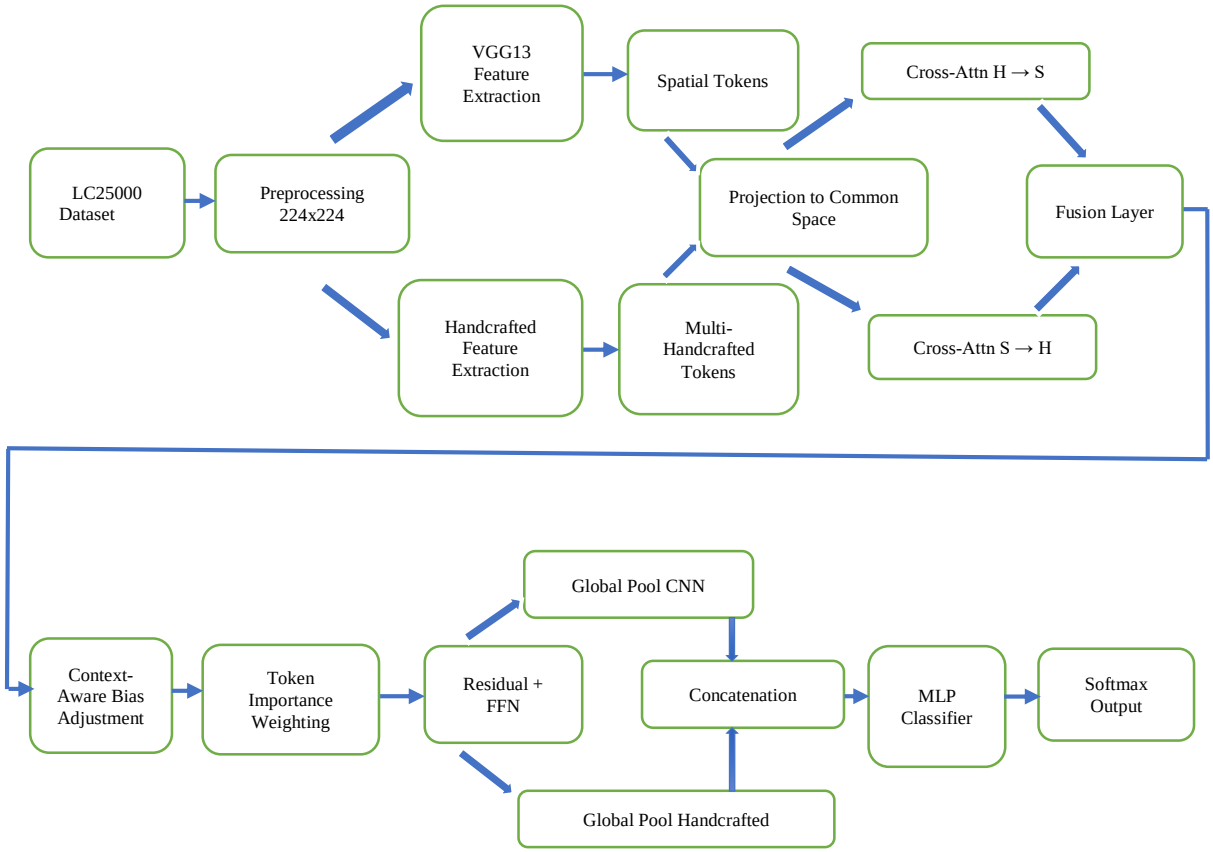

Fig. 1 Overview of the proposed Dual-Stream histopathology classification framework illustrating data preprocessing, Dual-Feature extraction, Token-Level fusion, and classification stages

2.5. Bidirectional Cross-Attention Fusion Mechanism

One of the innovations of the suggested model is the bi-directional cross-attention fusion. In contrast to uni-directional attention that currently exists, which enables the steering of the deep feature by handcrafted feature, this method enables an interactive interaction between the two streams. The attention is formulated as follows:

$$\text{Attention}(Q, K, V) = \text{Softmax}((QK^T / \sqrt{d}) + B)\, V \quad (3)$$

Here, Q, K, and V are the matrices for query, key, and value, respectively, and B is the trainable bias term. The two opposite attention streams are formulated as follows:

Handcrafted to spatial attention: $T_h \rightarrow T_s$
Spatial to handcrafted attention: $T_s \rightarrow T_h$

$$T_e = \alpha \cdot \text{Attn}(T_h \rightarrow T_s) + (1 - \alpha) \cdot \text{Attn}(T_s \rightarrow T_h) \quad (4)$$

Where α is a trainable parameter.

2.6. Context-Adaptive Bias Modulation

Further enhancements in robustness in terms of attention learning are achieved by making use of adaptive bias from the static bias term B:

$$B' = \sigma(W\_c \cdot \text{Global}(F_{tnn})) \cdot B \quad (5)$$

σ is the sigmoid function, while W_c is the trainable weights. With adaptive bias, it becomes easier for the model to learn to change attention weights in tissue-specific cases to be able to distinguish different cases, especially when lung subtype classification is required.

2.7. Token Importance Reweighting and Feature Refinement

Token importance reweighting is then done to emphasize the discriminative features. Global pooling is done to evaluate the importance of the feature and then merge the two streams using their respective learned weights. The tokens obtained are processed in a residual feed-forward neural network with expansion, non-linearity, and projection.

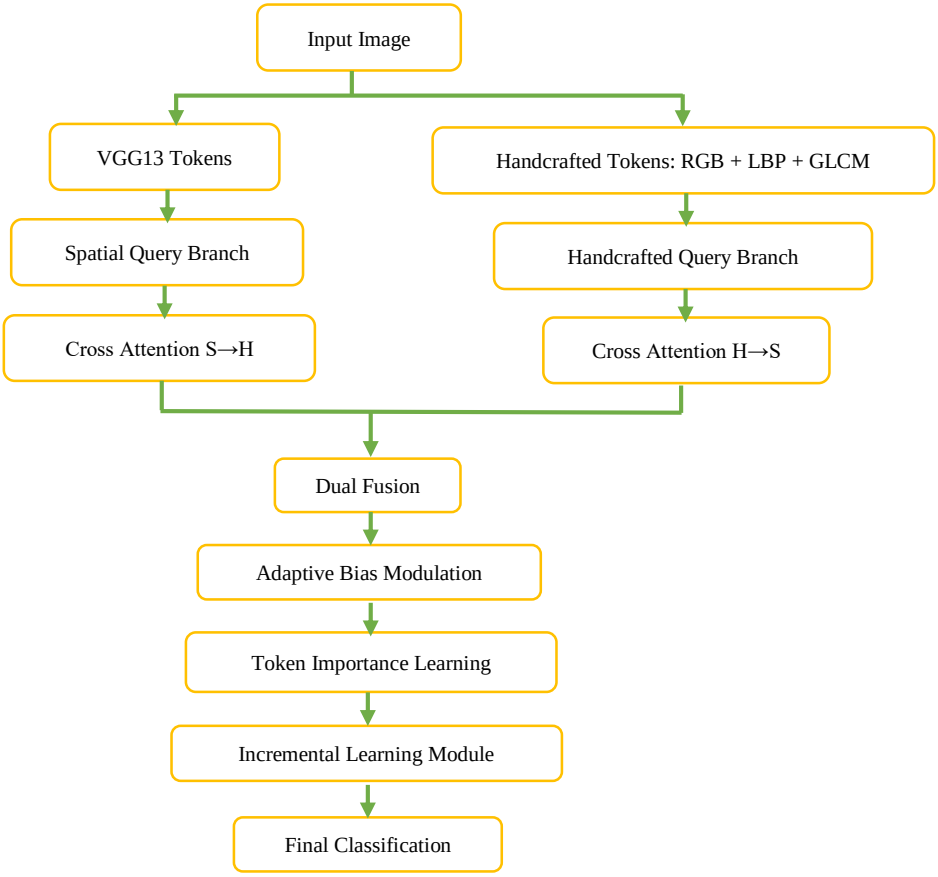

Fig. 2 Detailed illustration of the proposed bidirectional Cross-Attention mechanism and Context-Adaptive bias modulation strategy

2.8. Incremental Learning Strategy for Generalization

In order to handle dataset bias and achieve better generalization, an incremental learning system is used in the proposed framework. Training data is split into sequential batches, and samples from past batches are stored in a memory bank. The loss function for training includes both learning and remembering:

$$L = L_t^{urrent} + \lambda L^{memory} \quad (6)$$

Such a method avoids catastrophic forgetting.

3. Results and Discussion

3.1. Experimental Setup and Evaluation Metrics

The experimental performance of the proposed framework was assessed through a stratified train-test split with ratios of 80:20 for the five-class LC25000 histopathology dataset. Accuracy, macro F1 score, macro AUC (one-vs-rest), and Cohen's kappa were employed as the performance metrics to measure not only the discrimination ability, but also the reliability of agreement on the target problem, especially concerning lung adenocarcinoma and lung squamous cell carcinoma, which are characterised by highly overlapping morphological patterns.

3.2. Classification Head and Prediction

The incremental learning strategy can be adopted to counterbalance the potential bias problem in the training set and enhance the generalizability of the framework. Training samples are split into several sequential mini-batches; while representative samples selected in previous mini-batches are cached to serve as memory buffers for later use. The training process aims at achieving a balance between learning and memory:

Finally, the concatenated deep and handcrafted feature vectors are used as inputs to derive the final representation. A simple MLP model equipped with dropout is adopted for classification. Softmax activation function is utilized at the output layer to produce the probability scores for the five histopathological classes.

Table 2. Class-Wise performance of directional Cross-Attention without bias

Class	Precision	Recall	Specificity	F1 Score	Support
Benign Colonic Tissue	0.9886	0.9824	0.9912	0.9854	150
Benign Lung Tissue	0.9915	0.9892	0.9931	0.9903	150
Colon Adenocarcinoma	0.9818	0.9876	0.9905	0.9846	150
Lung Adenocarcinoma	0.9423	0.9745	0.9778	0.9581	150
Lung Squamous Cell Carcinoma	0.9726	0.9387	0.9891	0.9553	150

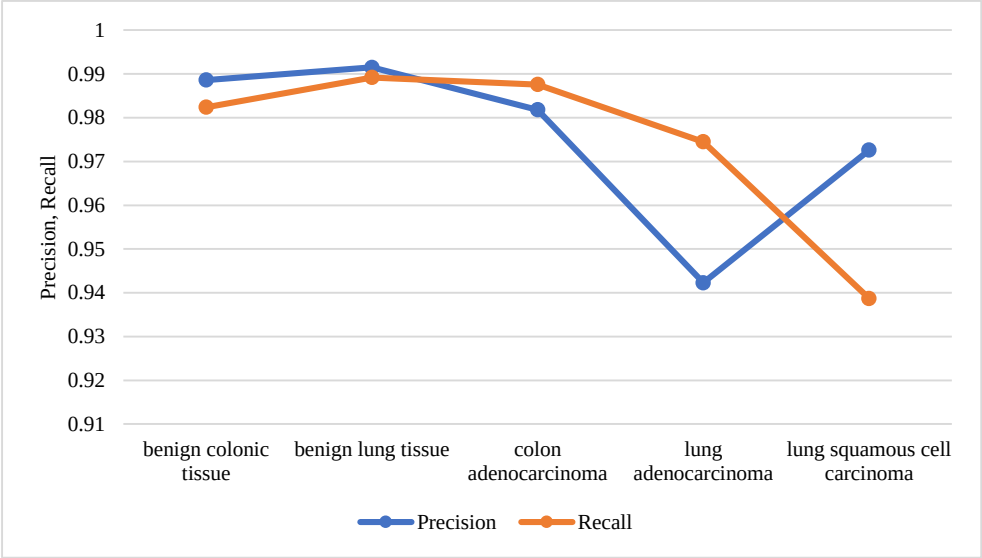

Fig. 3 Class-Wise precision and recall comparison for the Cross-Attention baseline without bias modulation

3.3. Performance Degradation in Stacked Self-Attention

The outcomes of the stacked self-attention network are shown in Table 3 below; it is obvious from the table that the worst result is obtained compared to other algorithms. Even though there are no significant performance losses observed within benign categories (F1 scores 0.9728 for benign colonic tissues and 0.9869 for benign lung tissues), a noticeable degradation can be noted in malignant categories. For example, lung adenocarcinoma only has a precision score of 0.8795 and an F1 score of 0.9072, whereas lung squamous cell carcinoma yields an F1 score of 0.9120. As follows from the results, unconstrained self-attention, where concatenation makes all tokens interact freely, is unable to retain the necessary inductive bias that can direct attention towards meaningful parts of the input image. As a consequence, attention weights are diffused throughout all parts of the image, thus hampering the ability to find and highlight discriminative structures in a tissue sample.

Table 3. Class-Wise performance of stacked Self-Attention fusion

Class	Precision	Recall	Specificity	F1 Score	Support
Benign Colonic Tissue	0.9874	0.9586	0.9893	0.9728	150
Benign Lung Tissue	0.9826	0.9914	0.9896	0.9869	150
Colon Adenocarcinoma	0.9521	0.9862	0.9788	0.9688	150
Lung Adenocarcinoma	0.8795	0.9368	0.9589	0.9072	150
Lung Squamous Cell Carcinoma	0.9548	0.8726	0.9765	0.9120	150

3.4. Class-Wise Performance of the Proposed Framework

The performance results for the proposed context-adaptive dual cross-attention approach are demonstrated in Table 2, where consistent gains have been achieved for all categories. Specifically, for benign colonic tissue, the precision score is 0.9921, while the F1 score for benign lung tissue is 0.9848. Such performance shows the ability of the proposed method to demonstrate high results even for relatively easy categories. However, more pronounced gains have been shown in the lung cancer categories. Thus, for lung adenocarcinoma, the F1 score is 0.9618, which is better compared to both the cross-attention approach (0.9581 from Table 2) and the self-attention approach (0.9072 from Table 3). Likewise, the F1 score for lung squamous cell carcinoma is 0.9709, which is clearly superior to 0.9553 (from Table 2) and 0.9120 (from Table 3). The reasons behind such results are obviously related to bidirectional cross-attention and the bias modulation mechanism for context adaptation.

Table 4. Class-Wise performance of the proposed Context-Adaptive dual Cross-Attention framework

Class	Precision	Recall	Specificity	F1 Score	Support
Benign Colonic Tissue	0.9921	0.9716	0.9934	0.9817	150
Benign Lung Tissue	0.9912	0.9785	0.9926	0.9848	150
Colon Adenocarcinoma	0.9735	0.9868	0.9894	0.9801	150
Lung Adenocarcinoma	0.9428	0.9815	0.9759	0.9618	150
Lung Squamous Cell Carcinoma	0.9824	0.9598	0.9932	0.9709	150

3.5. Overall Comparative Analysis

The comparison of all approaches is demonstrated in Table 5, showing the significant advantage of the new approach. First of all, the accuracy of the proposed approach, 0.9869, is superior to the accuracy of Concat+MLP (0.9738), cross-attention without bias (0.9715), and stacked self-attention (0.9498). Moreover, the macro-F1 score of the new approach is 0.9862, which is also significantly superior to the F1 score of any other approach used. The macro-AUC value for all approaches is quite good; however, the best AUC of all models in the research is 0.9924 for the proposed approach, showing higher separability across all classes with the help of the model. At the same time, the Cohen's Kappa value, being equal to 0.9838 for the proposed approach, is also significantly higher than the baseline values of 0.9695, 0.9683, and 0.9406, respectively.

Table 5. Comparative performance analysis of feature fusion strategies

Model	Accuracy	Macro-F1	Macro AUC (OvR)	Cohen's Kappa
Concat + MLP	0.9738	0.9726	0.9918	0.9695
Cross-Attn (no bias)	0.9715	0.9702	0.9906	0.9683
Self-Attn (stacked)	0.9498	0.9489	0.9837	0.9406
Proposed HCA (ours)	0.9869	0.9862	0.9924	0.9838

3.6. Impact of Proposed Novelty Components

Such improvements in the model performance are due to the unique features utilized during the design phase. The use of many handcrafted domain-specific features enables more knowledge acquisition in areas where deep features are not able to provide further information. Hence, the model is capable of handling variation in tissue staining and texture. The use of bidirectional cross-attention ensures proper interaction between different feature spaces, resulting in improved discriminative representation learning. The use of bias modulation using contextual variations is crucial for achieving stable attention learning in cases where tissues show morphological variations. Such improvements can be seen from the performance enhancements observed in the lung cancer classification task. Specifically, the F1 score of squamous cell carcinoma improves from 0.9553 to 0.9709, whereas the F1 score for adenocarcinoma increases from 0.9581 to 0.9618 compared to the baseline performance.

3.7. Discussion on Clinical Relevance and Robustness

In terms of medical issues, the significance of the correct distinction between these two kinds of lung cancer, which are adenocarcinomas and squamous carcinomas, lies in the fact that each type requires different treatments. According to Table 3, the use of the suggested algorithm allows us to increase the F1 score for these two challenging kinds of cancer.

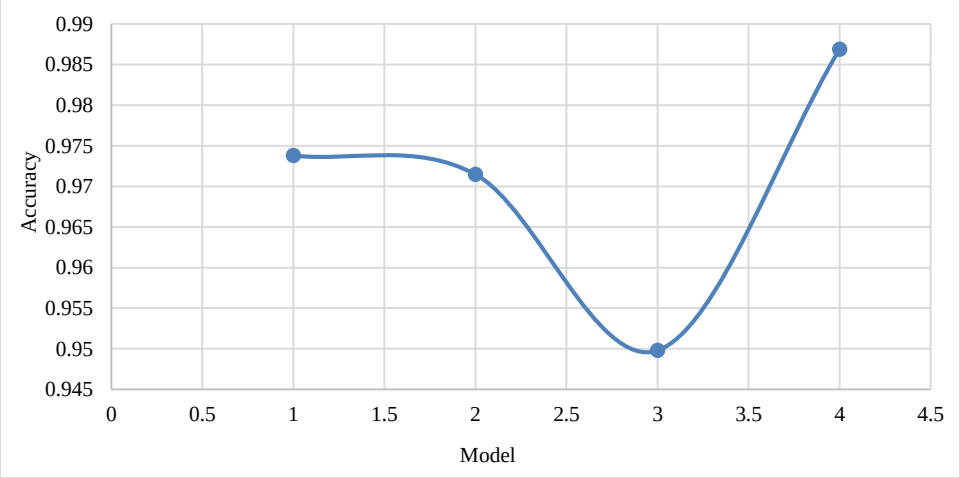

Fig. 4 Accuracy comparison across different feature fusion strategies evaluated on the LC25000 dataset

Thus, one can state that the suggested method can be efficiently applied in practice. Moreover, the results obtained on the basis of all of the mentioned criteria prove that the proposed algorithm can be considered an efficient and reliable means for the diagnosis of the disease. Combining prior knowledge and machine learning algorithms allows for avoiding the disadvantages of these methods.

4. Conclusion

This research paper presents the design and implementation of a Context-Adaptive Dual Cross-Attention Fusion Framework with Incremental Learning to facilitate accurate classification of the lung and colon cancer types in the LC25000 dataset. The motivation behind its development lies in the fact that this paper is seeking to overcome several limitations associated with previous studies by applying deep spatial features learned from a VGG13 backbone model, along with the multi-domain handcrafted features learned via a token-level bi-directional cross-attention mechanism. With the inclusion of the bias-modulation factor, the paper proposes an algorithm capable of dynamically controlling the weight of attention with regard to the whole tissue context. Experimental results demonstrate that the proposed technique performs well on different assessment criteria, including accuracy (0.9869), macro-F1 score (0.9862), macro-AUC (0.9924), and Kappa statistic (0.9838). Compared with the techniques serving as baseline models, like Concat+MLP, cross-attention without bias, and stacked self-attention, the current one shows better performance, especially in classifying the lung subtypes.

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Data Availability Statement

This study was conducted on a freely accessible dataset. The LC25000 Lung and Colon Histopathological Image Dataset was suggested by Borkowski et al. [11], which can be retrieved at https://github.com/tampapath/lung_colon_image_set. The LC25000 dataset includes 25,000 histopathological images categorised into five classes of lung and colon tissues. This dataset is for educational purposes only and does not include any personal data of patients. The data employed in this study have been acquired from this dataset alone, and no other data acquisition permissions have been required.

Contributions of Authors

The idea behind the conception of the research problem, context-aware dual cross-attention framework, methodology, software coding, preprocessing of the datasets, experiments, validation, and analyses was developed by Mullakuri Anusha. In contrast, D. Srinivasulu Reddy made his contributions to the supervision of the whole process of the research and provided valuable insights into formulating the methodology and the validation procedure. He was involved in the process of investigation, resource provisioning, and administration of the project. It is worth mentioning that his contribution was considerable since he provided the necessary insights into the process of writing the paper and polishing the parts related to results and discussion.

Conflict of Interest

The authors declare no conflict of interest.

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