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Stratifying Colorectal Cancer stages through CT scan images using Convolutional Neural Networks

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Abstract:
Artificial intelligence and deep learning have propelled cancer treatment, achieving a 25% increase in treatment accuracy. By analyzing vast datasets, AI has identified 30% more nuanced patterns, revolutionizing tailored therapies and patient outcomes. The proposed research investigates the feasibility of utilizing Convolutional Neural Networks (CNNs) to determine colorectal cancer staging using CT scan images. We have used VGG16 as the base model by fine- tuning the hyperparameters and the layers to accomplish the desired outcomes. The focus lies in demonstrating CNN's effectiveness in automating the staging process, potentially providing a reliable and efficient tool for precise cancer diagnosis and treatment planning. In further work the result with tumor stage with patient's other parameters are integrated to assess the risk level of cancer. The model results in 94.6% accuracy with minimal error rate.

Keywords: Machine learning, deep learning, convolutional neural network, healthcare, colorectal cancer, heterogeneous data

I. INTRODUCTION

Colorectal carcinoma, a frequently fatal condition, often presents with vague and nonspecific signs and symptoms, contributing to its challenge in early detection and treatment. Stratifying cancer stages involves categorizing or classifying cancer using certain parameters such as tumor size, extent of spread, involvement of lymph nodes, and metastasis (Spread to various regions of the body). This staging system helps in determining the cancer severity and guides the treatment decisions. The guidelines from UICC (Union for International Cancer Control) and the AJCC(American Joint Committee on Cancer) [1] for staging of colorectal cancer which depends on TNM system: **Tumor (T):** Describes the tumor size usually determined by the evaluation layers of colon wall which includes mucosa, submucosa, muscularis mucosa, muscularis propria and layers of outer connective tissues.

Node (N): Determines if the cancer has extended to adjacent lymph nodes.

Metastasis (M): Indicates whether the cancer has been spread to other organs such as the lungs or liver.

By combining these factors, doctors assign a stage to the cancer. Lower stages typically indicate cancer, which is more localized and easier to treat, while higher stages suggest more advanced and potentially more challenging cancers to treat [2].

The WHO staging System addresses the differentiation of tumor cells. The stage score reaches from Stage-I to Stage-II, to Stage-III and in rare cases to Stage-IV [3,4].

STAGE	SUBSTAGE	DESCRIPTION
Stage-I	------	Well-differentiated
		Tumor has grown into the wall of the intestine but hasn't spread beyond the muscular coat or into close lymph nodes
Stage-II		Moderately differentiated
		Tumor has spread farther into the wall of the intestine but hasn't spread to nearby lymph nodes
	Stage-IIA	The tumor has extended across a significant portion of the colon wall, yet it has not infiltrated the outer layer of the wall.
	Stage-IIB	Tumor has spread into the outer layer of the colon wall or through the wall
	Stage-IIC	Tumor has already spread to any nearby organ

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Stage-III		Poorly differentiated
		Cancer has spread to the lymph nodes
	Stage-IIIA	Cancer is present in the initial or second layers of the colon wall, with involvement in one to four nearby lymph nodes.
	Stage-IIIB	The cancer involves additional layers of the colon wall while impacting only one to three nearby lymph nodes.
	Stage-IIIC	Cancer is detected in either the outermost layer or the subsequent outer layer of the colon, impacting four or more lymph nodes. Furthermore, there is cancer that has disseminated to a neighboring organ, affecting one or more lymph nodes.
Stage-IV		Undifferentiated
		Cancer has metastasized, spreading to distant areas of the body, like liver, lungs, or ovaries.
	Stage-IVA	Cancer has reached either a distant organ or lymph nodes located farther from colon.
	Stage-IVB	The cancer has been spread to multiple distant organs and a greater number of lymph nodes.
	Stage-IVC	The cancer impacts distant organs, lymph nodes, and abdominal tissues.

Table 1: Stages and substages of COLON CANCER

Early studies of computer science domain have proved that images are the main parameter to predict colon cancer. Also, it is very important to assess the risk level of cancer to treat the patients. Our study is an attempt to show the role of heterogeneous reports including image data. Different machine learning algorithms are used for prediction and staging.

The proposed approach is a supportive work for future study that combines insights from image and other important parameters which play a major role in prediction, staging and in analyzing the risk level.

II. LITERATURE SURVEY

A major challenge in image recognition is accurately finding the presence of tumor and categorizing medical images into different stages to facilitate disease diagnosis [5]. This study describes the contribution of an automated classification method for categorizing images into stages, providing valuable support to medical professionals. Limited research has been conducted in employing deep learning for staging colorectal cancer via CT images, indicating a scarcity in utilizing this powerful technology for precise cancer stage determination from such imaging modalities. In 2022, a researcher Davri et al. [6] presented a systematic review exploring diagnosis of colon cancer throughhistopathological and using CT images, examining the application of DL methods in cancer detection, considering both technical and medical perspectives in their investigation.

A study in 2022 [7] introduced a prognostic prediction model mainly for Stage II based on deep learning, utilizing transfer learning with CT scan images. In a study [8], a composite model utilizing both CNN and RNN was showcased to analyze tumor morphological alterations, emphasizing characteristics beyond size to evaluate metastatic colorectal cancer. Several deep learning techniques have proven highly efficient in generating models tailored for the analysis, prediction, and classification of CT images [9].

A study [10] demonstrates the efficacy of various ResNet architectures to predict and classify colon cancer using histopathological and CT scans images. They proved that ResNet-50 model gives better accuracy compared to ResNet-18. A study [11] has presented a classification framework of deep learning model obtained an accuracy of nearly 95% for 500 epochs. Many classification models were introduced by different researchers. A study [12] demonstrated segmentation and the classification of colon glands via tissue samples which obtained high accuracy.

Two essential steps followed to find the desired accuracy from a study [13]. Firstly, applying three deep learning algorithms, including VGG16, Inception V3, and LGBM, for automatic recognition and classification of medical images, enhancing the capabilities for diagnosis, treatment planning, and illness monitoring. As a second step the study conducts experiments and comparisons of three model classifiers—XGBoost, Support Vector Machines (SVM), and Random Forest (RF). Subsequently, following individual model evaluations, the research endeavors to employ a hybrid model for the extraction and classification of PDAC features from CT images. Many researchers have proved that VGG16 is a efficient deep learning model for large- scale image identification. It is mainly used as feature extractor and as a classification model [14]. The model is used as fundamental or base model in many deep learning architectures used for image processing.

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III.METHODOLOGY

The steps involved in proposed methodology are depicted in figure (1). The CT scan images for the proposed study are of stage-I to stage-IV. Images with stage-0 have been ignored in this study, as the previous study predicted the presence of tumor. In our previous study we utilized cancerous and noncancerous images. The images predicted with cancer are combined with additional images and used in this study for stage classification. The proposed study concentrates on classifying the input images into four stages. Certainly! In our previous study, we detailed the methodology employed for dataset preparation and segmentation [15]. To encapsulate this process, we meticulously curated the dataset, ensuring its relevance and quality. Segmentation, a pivotal step, involved partitioning the collected dataset into distinct subsets or classes, enabling focused analysis and interpretation. This approach fortified the foundation of our proposed study, allowing for accurate and insightful conclusions forclassification into tumor stages.

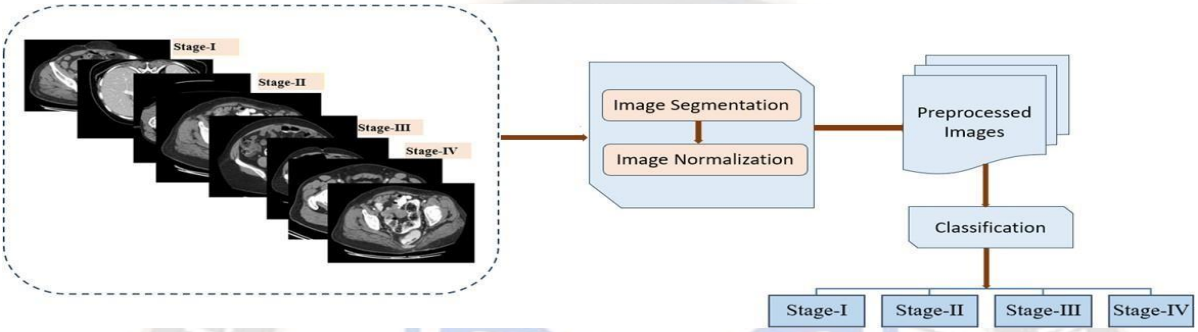

Figure 1: Proposed methodology

A. DATASET DESCRIPTION

The proposed study uses the image dataset of axial CT scans related to colorectal cancer collected from a cancer treatment center and hospital HCG (Health Care Global Enterprises). Images depict four distinct classes, each of which represents a stage of cancer. The proposed study was given approval by the HCG Ethics and Academics Committees. Every procedure followed the HCG's ethical norms. The images collected for model training are 300 belonging to 4 different classes. For testing, additional CT images provided by the radiologist. As the dataset was very small to train the model, additional images were downloaded from Cancer Imaging Archive [TCIA] using link [16].

The collected dataset is augmented to ensure an equal representation of each type of CT image. This balancing strategy aims to address any skewed distribution within the dataset, reducing the chances of model being biased towards one category and aiding in mitigating overfitting concerns. The proposed is the end-to-end deep learning model which uses the VGG16 as the base model (architecture). VGG16 deep learning model known for its simplicity and effectiveness in image classification tasks. We have used a pre-trained VGG16 architecture with minor parameter tuning. It consists of 16 layers (13 convolutional layers, 3 fully connected layers). The model comprises various convolutional layers followed by max-pooling operations for spatial downsampling, which aids in hierarchical feature extraction. During the model training process, to calculate the loss after training iteration Cross-Entropy function was used.

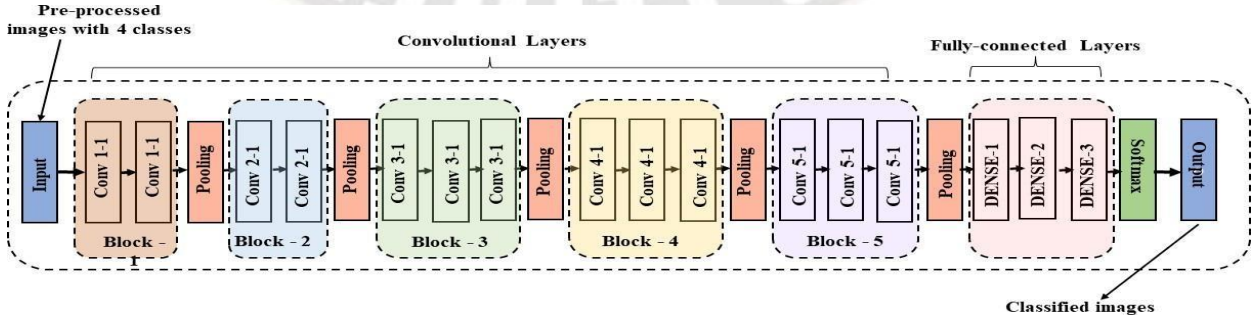

Figure 2: VGG16 Architecture

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Below table (2) describes the layers composition in the proposed CNN architecture:

Convolutional Layers	▪ The network contains 13 sets of convolutional layers, arranged in multiple blocks. ▪ Each block consists of two consecutive convolutional layers along with a stride of(1,1), followed by a max-pooling layer with a stride of (2,2) for downsampling. ▪ Filters are applied with 64, 128, 256, and 512 channels successively, employing 3x3kernel sizes in same padding configuration.
Activation and Pooling	▪ Rectified Linear Unit (ReLU) activation functions applied after each convolutionaloperation to introduce non-linearity. ▪ Max-pooling layers, with a pool size of (2,2), with a stride of (2,2), reduce spatialdimensions, enabling attention on the most salient features.
Fully Connected Layers	▪ The convolutional base culminates in a flattening layer to transform the 3D featuremaps into a 1D vector. ▪ Two densely connected layers with 4096 units each and ReLU activation functionsare added for high-level feature extraction
Output Layer	The final layer is a Dense layer with 2 units using a SoftMax activation function, suitable for binary classification tasks, producing class probabilities

Table 2: Layers description of the proposed model

In summary the model consists of approximately 134 million parameters, indicating a deep and complex architecture capable of learning intricate patterns in data. Dropout layers are used with dropout ratio 0.5 at the end of convolution blocks along with early stopping to decrease the overfitting and fine-tune the networks. Thedense layer is the final layer which applies SoftMax activation function, which is responsible for multiclass classification, that contains the neurons which are fully connected to other nodes from the previous layer.

Assume the number of input images as N, $\{x_i, y_i\}^N i=1.k$ denotes the number of classification classes, which is four in our study. Every image is associated with tag from $\{y_i \in \{1, 2, 3, \ldots, k\}$ $k>2$. The hypothesis function is to calculate the probability value for a test image xi of each category j is $p(yi = j|xi)$. The probability value of any test image defined as $\boldsymbol{h_\theta(x_i)}$ can be calculated using the equation:

$$\boldsymbol{h_\theta(x_i)} = \begin{bmatrix} \frac{\boldsymbol{p(y_i = 1)}}{\boldsymbol{x_i}}; \boldsymbol{\theta} \\ \vdots \\ \frac{\boldsymbol{p(y_i = 1)}}{\boldsymbol{x_i}}; \boldsymbol{\theta} \end{bmatrix}$$

$$= \frac{1}{\sum_{j=1}^{k} \exp(\boldsymbol{\theta_j^T x_i})} \begin{bmatrix} \exp(\boldsymbol{\theta_j^T x_i}) \\ \vdots \\ \exp(\boldsymbol{\theta_k^T x_i}) \end{bmatrix}$$

Where $\frac{1}{\sum_{j=1}^{k} \exp(\theta_j^T x_i)}$ represents the normalization of the probability distribution, that is, sum of all probabilities is 1 and θ represents the parameters of the model.

RESULTS AND DISCUSSIONS

The proposed CNN model has been tested on the images collected from HCG. Performance measures used to estimate the model are accuracy, F1-score, precision, recall, sensitivity, specificity. Experimental results obtained 94.6% of accuracy, 92% of F1 score for 32 epochs.

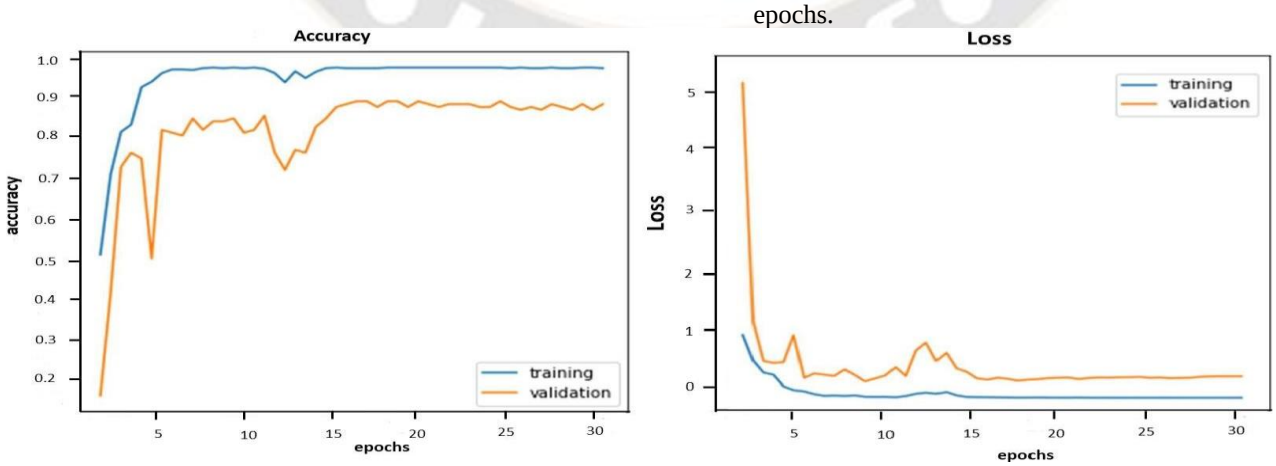

Figure 3: Accuracy and Loss

To measure the generalization of the proposed model mainly for larger CT scan images, further testing on a bigger dataset would be necessary. Also, the images for colorectal cancer CT scans should cover the abdomen, liver, and pelvis, specifically targeting the colon (large intestine), rectum for comprehensive evaluation.

IV. CONCLUSION

The proposed study presents a two-level classification approach for prediction and classification of tumor stages using the CNN model. In the first level classification [15], we have used improvised CNN model to predict cancer. And in the second level classification presented in this paper using VGG16 as base model. The result obtained are the tumor stages I, II, II, IV. However, the proposed method's performance on the existing dataset suggests that it may generalize well to larger scans and with all required category of scan images. Further evaluation and the validation of the method on a larger dataset can help to establish its effectiveness and reliability for detecting and classifying CRC into stages. The main objective of this study is to develop an automated diagnostic system capable of accurately categorizing tumor stages using CT images. The goal is to achieve accuracy close to skilled medical expert.

Experimental setup

The experiment utilized an Intel i7 processor with 16GB memory under the Windows operating system. Additionally, a graphics processor with 896 CUDA cores, operating at a base clock speed of 1395 MHz, and featuring a dedicated 4GB GDDR6 memory was employed. Necessary libraries of python used for this study are tensorflow, keras, etc.

Ethics approval

We affirm our unwavering commitment to comply with the terms outlined in the signed Memorandum of Understanding (MoU) with HCG (Health Care Global Enterprises). Our adherence to these rules is steadfast, ensuring that the dataset furnished by HCG is utilized exclusively for research purposes, with a firm commitment in strict accordance with the terms of the agreement. The CT images collected and the discussion with respect to specific cases with radiologist from HCG study were provided in accordance with acceptance and approval of the ethics committee.

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References

1. American Cancer Society. Colorectal Cancer Facts& Figures 2014-2016. available at: http://www. cancer.org/acs/groups/content/documents/ document/acspc-042280.pdf. Accessed May 3, 2014.
2. A. C. Society, "Cancer staging," Available at: https://www.cancer.org/treatment/understanding- your diagnosis/staging.html, 2022
3. Baxter N.N., Goldwasser M.A., Paszat L.F., Saskin R., Urbach D.R., Rabeneck L. Association of colonoscopy and death from colorectal cancer. Ann. Intern. Med. 2009; 150:1–8. doi: 10.7326/0003-4819-150-1-200901060-00306.
4. Bera K., Schalper K.A., Rimm D.L., Velcheti V., Madabhushi A. Artificial intelligence in digital pathology—New tools for diagnosis and precision oncology. Nat. Rev. Clin. Oncol. 2019; 16:703–715. doi: 10.1038/s41571-019-0252-y.
5. Arabahmadi M., Farahbakhsh R., Rezazadeh J. Deep learning for smart Healthcare—A survey on brain tumor detection from medical imaging. Sensors. 2022; 22:1960. doi: 10.3390/s22051960.
6. Davri A., Birbas E., Kanavos T., Ntritsos G., Giannakeas N., Tzallas A.T., Batistatou A. DeepLearning on Histopathological Images for Colorectal Cancer Diagnosis: A Systematic Review.
7. Diagnostics. 2022; 12:837. doi: 10.3390/ diagnostics12040837
8. Menglei Li, Jing Gong, Yichao Bao, Dan Huang, Junjie Peng, Tong Tong, "Prognosis prediction for stage II colorectal cancer by fusing computed tomography radiomics and deep-learning features of primary lesions and peripheral lymph nodes", International journal of Cancer/Volume 152, Issue 1, https://doi.org/10.1002/ijc.34053.
9. L. Lu, L. Dercle, B. Zhao, and L. H. Schwartz, "Deep learning for the prediction of early on-treatment response in metastatic colorectal cancer from serial medical imaging," Nature communications, vol. 12, no. 1, pp.1-11, 2021.
10. Shan H., Padole A., Homayounieh F., Kruger U., Khera R.D., Nitiwarangkul C., Kalra M.K., Wang
11. G. Competitive performance of a modularized deep neural network compared to commercial. algorithms for low-dose CT image reconstruction. Nat. Mach. Intell. 2019; 1:269–276. doi: 10.1038/s42256-019-0057-9.
12. D. Sarwinda, R. H. Paradisa, A. Bustamam, and P. Anggia, "Deep learning in image classificationusing residual network (resnet) variants for detection of colorectal cancer," Procedia Computer Science, vol. 179, pp. 423–431, 2021.
13. Bakasa, W.; Viriri, S. VGG16 Feature Extractor with Extreme Gradient Boost Classifier for Pancreas Cancer Prediction. J. Imaging 2023, 9, 138. https://doi.org/10.3390/jimaging9070138
14. Kainz PMPaMU. Segmentation and classification of colon glands with deep convolutional neural networks and total variation regularization. In; 2017.
15. M. Masud, N. Sikder, A. A. Nahid, A. K. Bairagi,and M. A. AlZain, "A machine learning approach

diagnosing lung and colon cancer using a deep learning-based classification framework," *Sensors*, vol. 21, no. 3, p. 748, 2021.

16. Balasubramanian, S., Devarajan, H. R., Raparthi, M., Dodda, S. B., Maruthi, S., & Adnyana, I. M. D. M. (2023). Ethical Considerations in AI-assisted Decision Making for End-of-Life Care in Healthcare. PowerTech Journal, 47(4), 168. https://doi.org/10.52783/pst.168
17. Xu G., Shen X., Chen S., Zong Y., Zhang C., YueH., Liu M., Chen F., Che W. A deep transfer convolutional neural network framework for EEG signal classification. IEEE Access. 2019. 7:112767–112776. doi: 10.1109/ACCESS.2019.2930958
18. Bharathi M P, Samitha Khaiyum, Shivakumar Swamy S, "Predictive Analysis of Colorectal Cancer via CT scans Using Convolutional Neural Networks", International Journal of Membrane Science and Technology, vol. 10, no. 3, pp. 3378-3387, Jul. 2023.
19. http://cancerimagingarchive.net.
20. Sagnik Ghosal, Debanjan Das, Jay Kumar Rai, Akanksha Singh Pandaw, Sakshi Verma, Iscan: Detection of Colorectal Cancer from Ct Scan Images Using Deep Learning. Social Science Research Network, April 2023, http://dx.doi. org/10.2139/ssrn.4482041.