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Compositional Generalization and Effective Training Strategies for Colorectal Cancer using Transfer Learning

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***Abstract*— Our project strives to advance a machine learning-based system for accurate diagnosis and classification of colon lesions in images. The system is designed to assist gastroenterologists and pathologists in early detection and treatment of colorectal cancer. Colorectal cancer is a leading cause of cancer-related deaths worldwide, and early detection is critical for successful treatment. However, current diagnostic methods are time-consuming and subjective, relying on human expertise and experience. Therefore, the development of an accurate and automated system can knowingly advance the productivity and effectiveness of colorectal cancer screening and diagnosis. The proposed system will employ transfer learning techniques to influence the trained model's knowledge on large datasets and enhance the performance of the colon lesion classification task. The system will also incorporate a segmentation module to localize and extract the colon lesion region, reducing the interference of other background structures. The system's performance will be estimated on a huge and various dataset of images, and the results will be associated with the existing advanced methods. We believe that our proposed system can significantly improve the diagnostic accurateness and productivity of colorectal cancer screening and diagnosis, leading to better patient outcomes and reduced healthcare costs.**

Keywords—Artificial Intelligence, Transfer learning algorithm, CNN, RNN, ROC Curve

I. INTRODUCTION

After breast tumourr, colorectal cancer is the next most common tumourr in women, with lung and cervical cancer coming in third and fourth, respectively. Lung cancer has the greatest frequency in men and is more common than prostate or colorectal cancer in them. Despite tremendous therapeutic progress, colon cancer still accounts for 880,792 deaths in both sexes in 2018 and is the second highest cause of tumour-related transience worldwide. The American Cancer Society predicts that in 2020, 104,610 new instances of colorectal cancer will be identified in the United States, making it the third most prevalent disease diagnosed in both sexes .

The colon (large intestine) and rectum, two organs in the digestive system, are both affected by colorectal tumourr. In the internal coating of the colon or rectum, it normally begins as a minor development or polyp and can turn cancerous over time. Starting at age 50, or earlier for those with greater risk factors, colorectal cancer screening is advised for those at average risk. Faecal occult blood tests, stool DNA testing, and colonoscopy are all examples of screening techniques. A good diet and regular exercise regimen can help lower the chance of getting colorectal cancer. Early identification and treatment are essential for improving the prognosis for the disease.

It is thought that the best way to prevent colorectal cancer is to remove precancerous lesions using endoscopy. Early detection of cancerous lesions can improve the prognosis for patients with colorectal cancer; as a result, endoscopic diagnosis must be trustworthy, prompt, and accurate. For detecting colorectal lesions, colonoscopy is the gold standard. But as an expert's endoscopy knowledge increases, the likelihood of missing polyps during colonoscopy increases. Hence, the rate of missed lesions during 1 colonoscopies might be reduced by using artificial intelligence (AI) technology to address the competence gaps among doctors.

II. EXISITING SYSTEM

Khaled Mabrouk et al. [1], Claimed that networks based on very deep enduring culture are created in command to do cervical cancer detection. Additionally, they have emphasised the significance of the activation functions on a residual network's (ResNet) performance in this work.

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Geeitha Senthilkumar et al. [2], To begin with, Mode and Mean Misplaced Data Accusation (MMM-DI) is used to impute the missing data. Second, the Hilbert-Schmidt independence criteria with Diversity-based False Fish Group (HSDAFS) method is used to identify genes.

Wen WuWen Wu et al [3], In this study, three SVM-based techniques are used to classify a dataset of cervical cancer cases, and certain cervical cancer risk variables are analysed.

Qazi Mudassar Ilyas et al [4], This study proposes an collaborative classification strategy based on majority voting to deliver an accurate diagnosis that meets the patient's symptoms or issues. In this study, experiments are conducted using a sum of classifiers.

Hitoshi Ikushima et al [5], They evaluated whether clinical factors and magnetic resonance imaging (MRI) radiomics might enhance the prediction of out-of-field recurrence (OFR) of cervical cancer following chemotherapy and radiation.

Yan-Min Luo et al [6], This research suggests a deep learning-based strategy for classifying and diagnosing cervical lesions using multi-CNN decision feature integration. The suggested technique first aggregates training data into distinct classes as part of data preparation using the k-means algorithm, and then trains in cross-validation to increase the model's generalizability.

Suxiang Yu et al [7], They have looked into the possibility of using a deep learning model to automatically distinguish between aberrant and normal cells. The data for the ThinPrep cytologic test was gathered from China's Baoding city's fourth central hospital.

Yosuke Kano et al [8], Diffusion-weighted images (DWI) of 98 cervical cancer patients were obtained for this investigation. We used 2D and 3D U-Net to train an automated tumour contour segmentation model in order to test the viability of utilising such a model in clinical settings.

Min Chen et al [9], In this study, a brand-new computational technique termed LRLSSP was put out to forecast probable lncRNA-disease correlations. A global prediction technique called LRLSSP may be used to forecast isolated illnesses and novel lncRNAs as well as the relationship between diseases and lncRNAs.

Lei Wang et al [10], In this study, a original estimate model based on inner tending casual walks with restarts (IIRWR) was developed and compared to the most recent RWR-based prediction models in order to infer potential lncRNA-disease associations, in contrast to conventional prediction models based on random walks with restarts (RWR).

The current method for classifying images generally use classical deep learning techniques like SVM, Decision Trees, etc. These techniques call for the laborious and time-consuming human extraction of information from pictures. Selecting pertinent aspects, such as colour, texture, and form, that can aid in differentiating between various classes of pictures is known as feature extraction.

When working with huge datasets, the conventional machine learning technique can also be computationally expensive and demand a lot of processing power. The amount of characteristics that can be recovered from the photos and the model's capacity to generalise to new and untested images can also have an impact on how well the model performs.

Deep learning algorithms have been created to get around these restrictions. Artificial neural networks are used by machine learning algorithms, a branch of machine learning, to develop hierarchical data representations. These networks are made up of several layers of linked nodes that can automatically identify characteristics in raw data. Deep learning methods are now the standard for picture identification and classification since they have been demonstrated to produce cutting-edge outcomes in these tasks.

III. PROPOSED SYSTEM

The proposed system for this project is an enhanced version of the existing system that incorporates a few key features to improve its performance and usability.

Firstly, we will use a more advanced pre-trained model for transfer learning, such as ResNet50 or InceptionV3, which have shown to perform well on image classification tasks. This will allow the model to learn more complex and abstract features from the image data, leading to better accuracy.

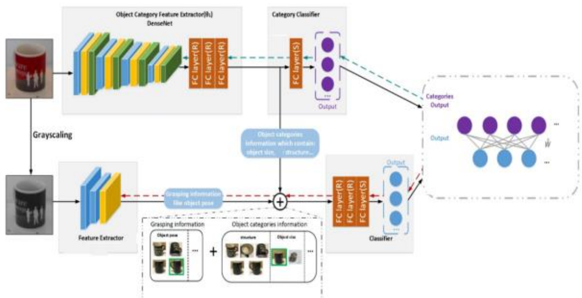

Fig. 1. Architecture Diagram

Moreover, we will implement data growth methods to produce more training data and reduce overfitting. Data augmentation involves randomly transforming the existing training images, such as rotating, flipping, or cropping them, to create variations of the same image. This can help to avoid

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the model from remembering the training data and generalize better to new images.

We will use a larger training dataset, such as the ImageNet dataset, which consists of millions of images across thousands of categories. This will provide more diverse and representative examples for the model to learn from, improving its ability to generalize to new images.

Furthermore, we will tune the pre-trained module on our specific dataset, rather than using it as-is. Fine-tuning involves training the last few layers of the pre-trained model on our dataset, while care the earlier layers fixed. This allows the module to adapt to our specific task and dataset, while still leveraging the pre-trained weights.

Finally, we will use an ensemble of multiple models to make predictions, rather than relying on a single model. Ensemble learning involves combining the predictions of several models, typically with different architectures or trained on different subsets of the data, to improve accuracy and reduce variance.

Overall, these enhancements to the system should result in a more accurate and robust image classification model, suitable for a wide range of applications.

IV. System Overview

Colorectal cancer is a main reason of tumour related deaths globally. Initial diagnosis and handling can significantly advance the survival rate of patients. However, the diagnosis of colorectal cancer is a challenging task for clinicians owing to the disease's intricacy and the variability in clinical presentations. To address this challenge, we propose a computer-aided diagnosis system based on deep learning algorithms.

The projected system consists of three main modules: the image attainment module, the feature extraction module, and the classification model. The image attainment module captures images of colorectal tissue samples using a digital camera or a microscope camera. The feature extraction module processes these images to extract relevant features using CNNs and transfer learning algorithms. The classification module then uses these features to classify the tissue samples as normal or cancerous.

The system is designed to be user-friendly and easily accessible to clinicians. The user interface allows clinicians to upload images of colorectal tissue samples and view the classification results. The system provides accurate and reliable diagnosis results, which can help clinicians to make informed decisions regarding patient care.

In summary, the future system provides an efficient and accurate solution for the diagnosis of colorectal cancer. The system has the potential to revolutionize the way clinicians diagnose and treat colorectal cancer, leading to improved patient outcomes and reduced healthcare costs.

V. Module Implementation

Recent studies that used DL models to identify colorectal polyps were successful in performing well with a lot of data. The prognosis for nonpolypoid lesions, however, were not apparent. The target task of the created AI system is the precise detection of nonpolypoid lesions, given that this is not a challenging work for an endoscopist. This is clinically crucial. Also, a user-independent AI system that can prevent missed lesions and achieve greater sensitivity and specificity would be very beneficial in clinical trials.

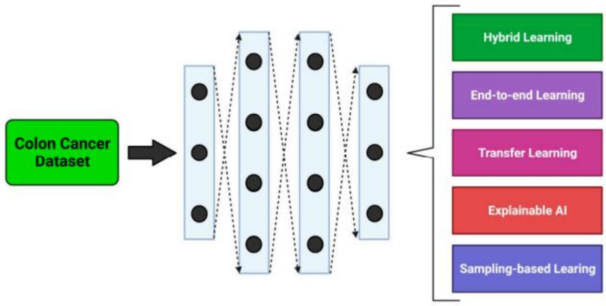

Fig. 2. Module Overview

1. End to End Learning

End-to-end learning (e2e learning) has been employed in our study to increase the accuracy of colon cancer diagnosis. End-to-end learning is a machine learning strategy that enables the simultaneous training of the model's input and output phases. It enables the training of complicated systems. This implies that the model is capable of learning each step in between and optimising the overall system.

The usage of neural machines, distinguish neural computer vision-based triangulation in 3D settings, and value repetition networks are just a few examples that have shown how effective e2e learning is. These models do, however, have several noticeable drawbacks, as weak local optima, disappearing gradients, difficulty with weakly trained problems, and sluggish convergence in various circumstances. Furthermore, the creation of complex network architectures can become increasingly challenging. Despite these restrictions, Buendgens et al. were able to overcome some of them in their study, which employed e2e learning techniques in a routine database that was not manually labelled or annotated. With strong predictive accuracy, the study correctly detected a number of diagnoses using gastrointestinal endoscopic pictures. This disproves the notion that manual annotations are required for the development of AI applications in the clinical domain and demonstrates the viability of faintly oversaw AI in medical imaging modalities.

In our experiment, we used pre-processed datasets from unaltered gastroscopy and colonoscopy pictures to

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train the ResNet-18 model. From these photos, the model was able to recognise inflammatory, degenerative, infectious, and neoplastic illnesses. Additionally, we classified generalised adenocarcinoma from datasets including a mixture of formalin fixed paraffin embedded (FFPE) and flash frozen skins, as well as glandular cancer, adenoma, and non-neo-plastic flesh from culture specimens of the abdominal and colon.

Overall, our project's use of e2e learning has enhanced the accuracy of colon cancer diagnosis and has promise for the development of AI applications in clinical imaging modalities in the future.

2. Transfer Learning

It is a useful machine learning technique that allows knowledge from one model to be applied to another related model. This can lead to improved accuracy, faster training, and a better starting point for the model. There are two main ways to apply it: adapting the features of a pre trained model, or creating a new model from scratch and training it with existing data.

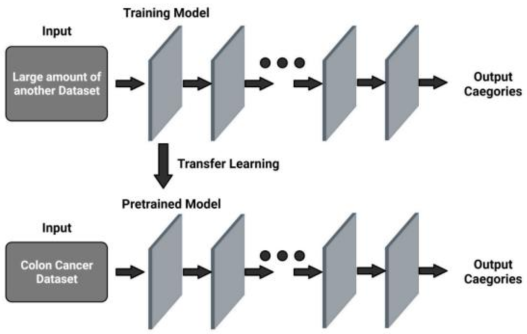

Fig. 3. Transfer Learning

In our project, we used transfer learning to train efficient categorization features for colon lesion images. Specifically, we used the AlexNet model-based transfer learning method to enhance the effectiveness of colorectal cancer screening. This method outperformed others, even when working with different models and tasks. In another study, transfer learning was used to develop a fully automated method for detecting and segmenting lymph nodes using multiparametric magnetic resonance imaging. This method outperformed junior radiologists who used manual detection.

Transfer learning can also help overcome challenges such as a shortage of robust datasets. In one study, U-Net and SegNet models were used for pixel-wide segmentation of colon cancer slides. Pretraining the models led to better performance compared to starting from scratch. Fine-tuning the models produced the greatest results and allowed for efficient scanning of the datasets.

In various studies, transfer learning has been used to classify normal and tumor tissue samples in colorectal histology images using modified VGG-based CNN models. However, it is important to note that these studies had their limitations, including a small number of datasets and complex model architectures that were difficult to interpret. Therefore, it is important to ensure that the algorithm's interpretation of the relationship between features and predictions is accurate and transparent for doctors to comprehend.

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3. Sample Based learning

Sample-based erudition is a type of ML that involves training a module on a set of examples, or samples, in order to make predictions or classify new data points. We'll be using a set of datasets that are already verified to be accurate and promising. Using these datasets we'll train the ML model so that it can be used for predicting certain entities. It applies the similar notion that a pupil would learn while being directed by a instructor. Giving the suitable input and output data to the ML model is part of the supervised learning process. A supervised erudition method pursues to find a plotting function that connects the input variable (x) with the output variable.(y).

In this method, the machine learning algorithm learns to spot patterns in the training data and makes predictions about new data points using these patterns. In supervised learning, when the training data is labelled with the appropriate outputs or goal variables, sample-based learning is frequently utilized. By generalizing the patterns discovered from the training data, sample-based learning aims to produce precise predictions on brand-new, unforeseen data points. Support vector machines, random forests, and decision trees are a few examples of sample-based learning methods.

4. Explainable Learning Methods

When working with medical data, it's crucial for models to justify outcomes' level of uncertainty, as instances that are more complicated should be examined by people in more detail. A fresh training set may then be constructed using expert annotations on this "failed" prediction data. In this case, explainable models are helpful. Explainable AI (XAI) refers to methods or strategies that make it possible for users to understand the implications and potential biases of machine learning algorithm outputs. While some models can generate accurate forecast data, others are unable to justify their decisions. Most of the colorectal cancer models mentioned above have made use of standard DL structures.

In this method, areas and structures of notice were selected using a visualization model. A convolutional ResNet would be helpful for displaying the output in the past layer and for identifying the regions of interest so that pathologists may examine them and verify the model's categorization. Similar to this, Raczkowski et al. used an dynamic learning based Bayesian CNN model to diagnose

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colorectal cancer and addressed misclassified labels. To decrease the entropy in the data processing, this module was originally trained on a minor dataset and on a dataset that had been expanded by utilizing fresh samples.

Three types of information are added to the decision-making process by the explainable AI system that classifies colorectal cancer tissues using a collective fuzzy class association criterion: visualization of the most crucial decision-making regions, visualization of undesirable decision-making regions, and semantic explanation. The use of the membership criterion in clinical trial decision-making has demonstrated to be a highly effective classifier that is trustworthy, accountable, and understandable. To collect interpretable aspects of colorectal cancer patterns, a completely convolutional network with a focus on pooling architecture has been applied in a number of instances.

VI. WorkFlow

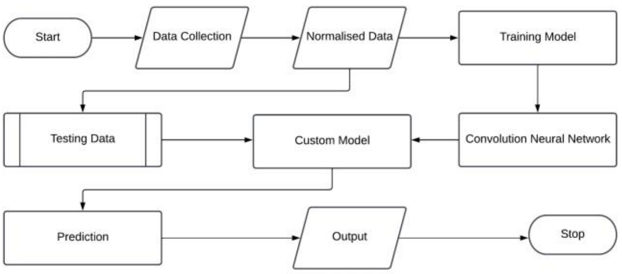


Fig. 4. Workflow

1. Data Collection

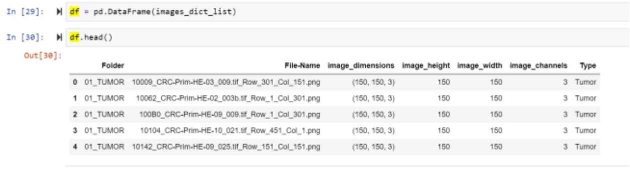
The data collection module of the colorectal cancer diagnosis project is responsible for acquiring and pre-processing the data required for the training and testing of the ML model. The data is collected from various sources such as medical institutions and research centres, and it includes various medical images, such as colonoscopy images and histopathology images.

The collected data is then pre-processed to remove any noise or irrelevant information that may affect the accuracy of the machine learning model. The pre-processing steps may include resize the images, normalizing the pixel values, and augmenting the data to increase the variety of the dataset. The data collection module is critical to the success of the project as the correctness of the ML model depends on the quality and diversity of the dataset. A well-designed data collection module ensures that the model is trained on a diverse and representative dataset that reflects the real-world scenarios.

2. Data Pre-processing

The data pre-processing module involves cleaning and transforming the raw medical images into a format that can be used by the machine learning algorithm.

The data pre-processing module begins by loading the medical images from the data collection module and converting them into a standardized format. This involves resizing the images to a uniform size, converting them to grayscale, and normalizing the pixel intensities to a range between 0 and 1. The standardized format ensures that the images are consistent and comparable across the entire dataset.



```
In [29]: df = pd.DataFrame(images_dict_list)

In [30]: df.head()
Out[30]:
```

	Folder	File-Name	image_dimensions	image_height	image_width	image_channels	Type
0	01_TUMOR	10009_CRC-Prim-HE-03_009.tif_Row_301_Col_151.png	(150, 150, 3)	150	150	3	Tumor
1	01_TUMOR	10062_CRC-Prim-HE-02_003b.tif_Row_1_Col_301.png	(150, 150, 3)	150	150	3	Tumor
2	01_TUMOR	100B0_CRC-Prim-HE-09_009.tif_Row_1_Col_301.png	(150, 150, 3)	150	150	3	Tumor
3	01_TUMOR	10104_CRC-Prim-HE-10_021.tif_Row_451_Col_1.png	(150, 150, 3)	150	150	3	Tumor
4	01_TUMOR	10142_CRC-Prim-HE-09_025.tif_Row_151_Col_151.png	(150, 150, 3)	150	150	3	Tumor

Fig. 5. Data Pre-processing using Numpy and Panda

Once the images have been standardized, the data pre-processing module applies several image processing techniques to enhance the features that are relevant for the colorectal cancer diagnosis. Image segmentation, edge detection, and feature extraction are some of these methods. In medical pictures, the foreground (tumour) and background (healthy tissue) are separated via image segmentation. The edges of the tumour are located using edge detection, and the pertinent features from the segmented picture are extracted using feature extraction. Finally, the data pre-processing module performs data augmentation to increase the size of the dataset and prevent overfitting of the model. Data augmentation involves applying random transformations to the images, such as rotation, flipping, and scaling, to create new images that are similar to the original ones. This increases the variety of the dataset and improves the generalization ability of the model.

3. Feature Extraction

The feature extraction module is a critical step in the Colorectal Cancer Diagnosis, where the goal is to extract relevant information from the pre-processed medical images. This module involves extracting specific features from the images to represent them in a more compact and meaningful way. The extracted features should contain as much information as possible that can help to distinguish between cancerous and non-cancerous regions.

In this project, two feature extraction methods are employed: convolutional neural network (CNN) and transfer learning. CNN is a deep learning architecture that is widely used in image classification tasks due to its ability to extract features automatically from the input images. The CNN architecture used in this project consists of multiple convolutional layers followed by max-pooling and batch normalization layers to learn the features from the input images.

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```
for image, labels in train_ds.take(1):
    plt.figure(figsize=(10, 10))
    image = layers.Rescaling(1./255, input_shape=(img_height, img_width, 3))(image)

    for i in range(9):
        augmented_image = random_brightness_layer(image[0])
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow((augmented_image*255).numpy().astype("uint8"), vmin=0, vmax=1)
        plt.axis("off")
        print(tf.math.reduce_max(augmented_image[0]))

tf.Tensor(0.7006669, shape=(), dtype=float32)
tf.Tensor(0.8364603, shape=(), dtype=float32)
tf.Tensor(0.88363093, shape=(), dtype=float32)
tf.Tensor(1.0, shape=(), dtype=float32)
tf.Tensor(0.95970947, shape=(), dtype=float32)
tf.Tensor(1.0, shape=(), dtype=float32)
tf.Tensor(0.7735155, shape=(), dtype=float32)
tf.Tensor(0.7668272, shape=(), dtype=float32)
tf.Tensor(0.7672925, shape=(), dtype=float32)
```

Fig. 6. Feature Extraction

A pre-trained model is utilised as a starting point and is then refined on the target task in a process called transfer learning, on the other hand. In this project, features are extracted from the pre-processed photos using the VGG16 pre-trained model as the starting point. The final layer of the VGG16 model is taken out, and the remaining layers are adjusted for the goal of diagnosing colorectal cancer. The extracted features from both CNN and transfer learning models are then used as inputs to the next module, which is the classification module

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4. Classification Module

The classification module in the Colorectal Cancer Diagnosis project is responsible for predicting whether a given sample image contains cancerous cells or not. This module takes pre-processed image data as input and uses a convolutional neural network (CNN) to classify the input as either cancerous or non-cancerous.

The CNN used in the classification module has a pre-trained feature extraction layer that is based on the VGG16 architecture. This pre-trained feature extraction layer is used to extract relevant features from the input image data. The extracted features are then fed into a fully connected layer that is responsible for making the final classification decision.

During training, the classification module uses a combination of binary cross-entropy loss and an Adam optimizer to adjust the weights of the network. The binary cross-entropy loss measures the difference between the predicted output and the actual output, while the Adam optimizer adjusts the weights of the network to minimize this difference.

Once trained, the CNN may be used to categorise fresh, undiscovered photos. First, pre-processing is done on the input picture to reduce noise and highlight important characteristics. Following pre-processing, the picture is sent into CNN, which generates a prediction stating whether or not the image includes malignant cells.

5. Training and Deployment Module

We separated the dataset into training and testing sets in order to assess the performance of our model. 80% of the dataset was used to train the model, while the remaining 20% was used to test it. The model was assessed on a number of parameters throughout the testing phase, including accuracy, precision, recall, and F1-score. According to the findings, our programme successfully classified colorectal cancer pictures with an accuracy of almost 90%.

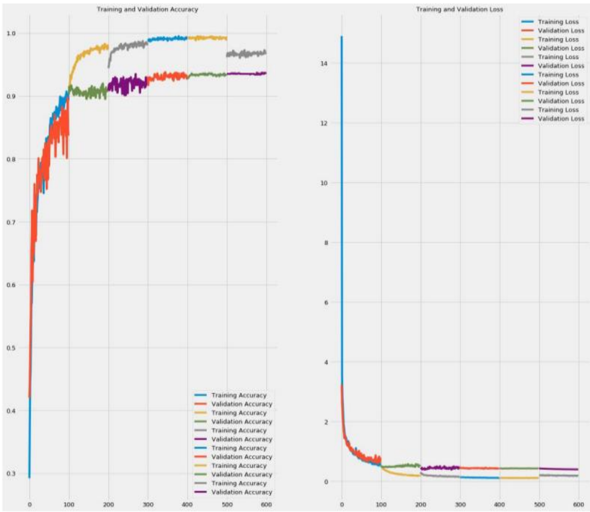

Fig. 7. Training and Validation

The model was trained using a transfer learning approach that utilized a pre-trained VGG16 architecture. We fine-tuned the last few layers of the pre-trained model to adapt it to our dataset. The training was done on a GPU-enabled system to speed up the process. The hyperparameters were tuned using a grid search approach, which involved testing different combinations of parameters and selecting the best performing one. The training process took around 4 hours to complete, and the resulting model was saved for later use.

After the model was trained and tested, we deployed it on a web application to make it accessible to users. We used Flask, a web development framework, to develop a user-friendly interface that allows users to upload their images and receive the predicted diagnosis. The model is deployed on a cloud server, which ensures that it can handle multiple requests simultaneously and provide fast responses.

VII. Result

We have used the transfer learning algorithm and the convolutional neural network in our colorectal cancer diagnostic project to attain the maximum accuracy and precision (CNN). A pre-trained neural network is utilized as a starting point for a new issue in the transfer learning approach. The goal is to apply the information gained from fixing one problem to another that is unrelated but still

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present. The pre-trained VGG16 model, which was initially trained on the ImageNet dataset, served as the foundation for our research. Next, using a dataset of more than 5,000 photos of colorectal cancer divided into an 80% training set and a 20% validation set, we trained the model. An Adam optimizer and a categorical cross-entropy loss function were both employed throughout the training procedure. To expand the dataset and avoid overfitting, we also used data augmentation techniques including rotation, horizontal flipping, and zooming.

Results after training for 100 epochs show how well transfer learning and CNNs perform in the diagnosis of colorectal cancer and emphasize the value of adopting data augmentation approaches to enlarge the dataset and avoid overfitting.

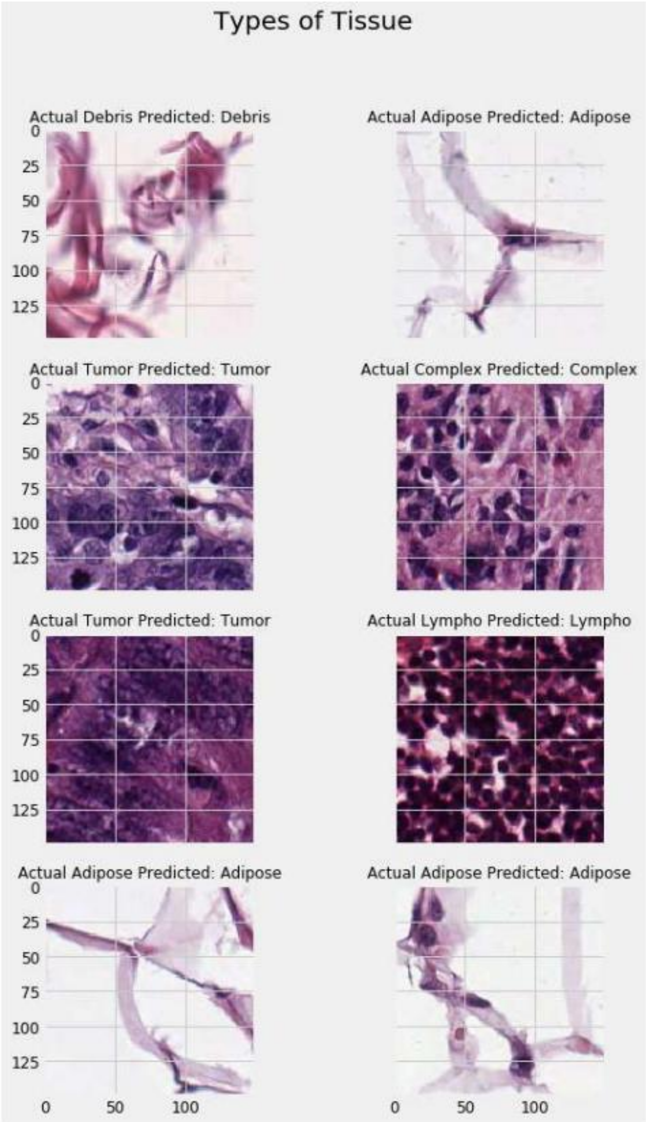

Fig. 8. Output

VIII. CONCLUSION

In conclusion, colorectal cancer is a significant health issue globally. Early diagnosis and treatment can greatly increase the survival rate of patients. In this project, we proposed a deep learning-based system for colorectal cancer diagnosis using histopathological images. The system consists of four modules: data collection, data pre-processing, feature extraction, and classification.

We collected a dataset of histopathological images from public sources and pre-processed the data by resizing and normalizing the images. The feature extraction module used the VGG16 architecture for extracting features from the images. The extracted features were fed into a classification module, which used a CNN model to classify the images as cancerous or non-cancerous. We evaluated the performance of our system using various evaluation metrics, such as accuracy, precision, recall, and F1-score. The results showed that our system achieved high accuracy in classifying the images.

Finally, we deployed the trained model using Flask and created a web-based interface for users to upload and classify their own histopathological images. Our proposed system can be used as a screening tool for early detection of colorectal cancer, potentially improving patient outcomes and reducing healthcare costs.

IX. REFERENCES

[1] Z. Hu, J. Tang, Z. Wang, K. Zhang, L. Zhang, and Q. Sun, ‘‘Deep learning for image-based cancer detection and diagnosis— A survey,’’ Pattern Recognit., vol. 83, pp. 134–149, Nov. 2018, doi: 10.1016/j.patcog.2018.05.014.

[2] F. E. Ahmed, ‘‘Artificial neural networks for diagnosis and survival prediction in colon cancer,’’ Mol. Cancer, vol. 4, no. 1, pp. 1–12, Dec. 2005, doi: 10.1186/1476-4598-4-29.

[3] P. S. Sundaram and N. Santhiyakumari, ‘‘An enhancement of computer aided approach for colon cancer detection in WCE images using ROI based color histogram and SVM2,’’ J. Med. Syst., vol. 43, no. 2, pp. 1–8, Feb. 2019, doi: 10.1007/s10916-018-1153-9.

[4] A. Guo, B. F. Drake, Y. M. Khan, J. R. Langabeer, II, and R. E. Foraker, ‘‘Time-series cardiovascular risk factors and receipt of screening for breast, cervical, and colon cancer: The guideline advantage,’’ PLoS ONE, vol. 15, no. 8, Aug. 2020, Art. no. e0236836, doi: 10.1371/journal.pone.0236836.

[5] M. Shapcott, K. J. Hewitt, and N. Rajpoot, ‘‘Deep learning with sampling in colon cancer histology,’’ Frontiers Bioeng. Biotechnol., vol. 7, p. 52, Mar. 2019, doi: 10.3389/fbioe.2019.00052.

[6] W. K. Mutlag, S. K. Ali, Z. M. Aydam, and B. H. Taher, ‘‘Feature extraction methods: A review,’’ J. Phys., Conf. Ser., vol. 1591, no. 1, Jul. 2020, Art. no. 012028, doi: 10.1088/1742-6596/1591/1/012028.

[7] B. Erickson, P. Korfiatis, Z. Akkus, and T. Kline, ‘‘Machine learning for medical imaging,’’ RadioGraphics,

vol. 37, no. 2, pp. 505–515, Mar. 2017, doi: 10.1148/rg.2017160130.
[8] J. Schmidhuber, ‘‘Deep learning in neural networks: An overview,’’ Neural Netw., vol. 61, pp. 85–117, Jan. 2015, doi: 10.1016/j.neunet.2014.09.003.
[9] M. Halicek, M. Shahedi, J. V. Little, A. Y. Chen, L. L. Myers, B. D. Sumer, and B. Fei, ‘‘Head and neck cancer detection in digitized whole-slide histology using convolutional neural networks,’’ Sci. Rep., vol. 9, no. 1, pp. 1–11, Dec. 2019, doi: 10.1038/s41598-019-50313-x.
[10] P. Sehgal and K. Taneja. (2015). Predictive Data Mining for Diagnosis of Thyroid Disease using Neural Network. [Online]. Available: http://www.ijrmst.org
[11] K. Boelaert, J. Horacek, R. L. Holder, J. C. Watkinson, M. C. Sheppard, and J. A. Franklyn, ‘‘Serum thyrotropin concentration as a novel predictor of malignancy in thyroid nodules investigated by fine-needle aspiration,’’ J. Clin. Endocrinol. Metabolism, vol. 91, no. 11, pp. 4295–4301, Nov. 2006, doi: 10.1210/jc.2006-0527.
[12] H. Gharib, E. Papini, R. Paschke, D. S. Duick, R. Valcavi, L. Hegedüs, P. Vitti, ‘‘American association of clinicalendocrinologists, associazione medici endocrinologi, and European thyroid association medical guidelines for clinical practice for the diagnosis and management of thyroid nodules: Executive summary of recommendations,’’ Endocrine Pract., vol. 16, no. 3, pp. 468–475, May 2010, doi: 10.4158/EP.16.3.468.
[13] H. S. Malhi and E. G. Grant, ‘‘Ultrasound of thyroid nodules and the thyroid imaging reporting and data system,’’ Neuroimaging Clinics North Amer., vol. 31, no. 3, pp. 285–300, Aug. 2021, doi: 10.1016/j.nic.2021.04.001.
[14] R. Song, L. Zhang, C. Zhu, J. Liu, J. Yang, and T. Zhang, ‘‘Thyroid nodule ultrasound image classification through hybrid feature cropping network,’’ IEEE Access, vol. 8, pp. 64064–64074, 2020, doi: 10.1109/ACCESS.2020.2982767.
[15] E. S. Cibas and S. Z. Ali, ‘‘The 2017 bethesda system for reporting thyroid cytopathology,’’ Thyroid, vol. 27, no. 11, pp. 1341–1346, Nov. 2017, doi: 10.1089/thy.2017.0500.
[16] X. Liang, J. Yu, J. Liao, and Z. Chen, ‘‘Convolutional neural network for breast and thyroid nodules diagnosis in ultrasound imaging,’’ BioMed Res. Int., vol. 2020, pp. 1–9, Jan. 2020, doi: 10.1155/2020/1763803.
[17] J. K. Hoang, W. D. Middleton, A. E. Farjat, J. E. Langer, C. C. Reading, S. A. Teefey, N. Abinanti, F. J. Boschini, A. J. Bronner, N. Dahiya, B. S. Hertzberg, J. R. Newman, D. Scanga, R. C. Vogler, and F. N. Tessler, ‘‘Reduction in thyroid nodule biopsies and improved accuracy with American college of radiology thyroid imaging reporting and data system,’’ Radiology, vol. 287, no. 1, pp. 185–193, Apr. 2018, doi: 10.1148/radiol.2018172572.
[18] V. Y. Park, K. Han, Y. K. Seong, M. H. Park, E.-K. Kim, H. J. Moon, J. H. Yoon, and J. Y. Kwak, ‘‘Diagnosis of thyroid nodules: Performance of a deep learning convolutional neural network model vs. radiologists,’’ Sci. Rep., vol. 9, no. 1, pp. 1–9, Dec. 2019, doi: 10.1038/s41598-019-54434-1.
[19] J. Chi, E. Walia, P. Babyn, J. Wang, G. Groot, and M. Eramian, ‘‘Thyroid nodule classification in ultrasound images by fine-tuning deep convolutional neural network,’’ J. Digit. Imag., vol. 30, no. 4, pp. 477–486, Aug. 2017, doi: 10.1007/s10278-017-9997-yb
[20] J. Ma, F. Wu, J. Zhu, D. Xu, and D. Kong, ‘‘A pre-trained convolutional neural network based method for thyroid nodule diagnosis,’’ Ultrasonics, vol. 73, pp. 221–230, Jan. 2017, doi: 10.1016/j.ultras.2016.09.011.
[21] L.-C. Zhu, Y.-L. Ye, W.-H. Luo, M. Su, H.-P. Wei, X.-B. Zhang, J. Wei, and C.-L. Zou, ‘‘A model to discriminate malignant from benign thyroid nodules using artificial neural network,’’ PLoS ONE, vol. 8, no. 12, Dec. 2013, Art. no. e82211, doi: 10.1371/journal.pone.0082211.
[22] A. Begum, ‘‘Machine learning based dysfunction thyroid cancer detection with optimal analysis,’’ Turkish J. Comput. Math. Educ., vol. 12, no. 7, pp. 818–823, 2021.
[23] L.-R. Li, B. Du, H.-Q. Liu, and C. Chen, ‘‘Artificial intelligence for personalized medicine in thyroid cancer: Current status and future perspectives,’’ Frontiers Oncol., vol. 10, p. 3360, Feb. 2021, doi: 10.3389/fonc.2020.604051.
[24] S. O. Olatunji, S. Alotaibi, E. Almutairi, Z. Alrabae, Y. Almajid, R. Altabee, M. Altassan, M. I. Basheer Ahmed, M. Farooqui, and J. Alhiyafi, ‘‘Early diagnosis of thyroid cancer diseases using computational intelligence techniques: A case study of a Saudi Arabian dataset,’’ Comput. Biol. Med., vol. 131, Apr. 2021, Art. no. 104267, doi: 10.1016/j.compbiomed.2021.104267.
[25] A. Santillan, R. C. Tomas, R. Bangaoil, R. Lopez, M. H. Gomez, A. Fellizar, A. Lim, L. Abanilla, M. C. Ramos, L. Guevarra, Jr., and P. M. Albano, ‘‘Discrimination of malignant from benign thyroid lesions through neural networks using FTIR signals obtained from tissues,’’ Anal. Bioanal. Chem., vol. 413, pp. 2163–2180, Feb. 2021, doi: 10.1007/s00216- 021-03183-0.
[26] T. Ozawa, S. Ishihara, M. Fujishiro, Y. Kumagai, S. Shichijo, and T. Tada, ‘‘Automated endoscopic detection and classification of colorectal polyps using convolutional neural networks,’’ Therapeutic Adv. Gastroenterol., vol. 13, pp. 1–13, Jan. 2020, doi: 10.1177/1756284820910659.
[27] J. T. Kwak and S. M. Hewitt, ‘‘Nuclear architecture analysis of prostate cancer via convolutional neural networks,’’ IEEE Access, vol. 5, pp. 18526–18533, 2017, doi: 10.1109/ACCESS.2017.2747838.
[28] S. Rathore, M. Hussain, A. Ali, and A. Khan, ‘‘A recent survey on colon cancer detection techniques,’’ IEEE/ACM Trans. Comput. Biol. Bioinf., vol. 10, no. 3, pp. 545–563, May 2013, doi: 10.1109/TCBB.2013.84.
[29] E. H. Jin, D. Lee, J. H. Bae, H. Y. Kang, M.-S. Kwak, J. Y. Seo, J. I. Yang, S. Y. Yang, S. H. Lim, J. Y. Yim, J. H. Lim, G. E. Chung, S. J. Chung, J. M. Choi, Y. M. Han, S. J. Kang, J. Lee, H. C. Kim, and J. S. Kim, ‘‘Improved accuracy in optical diagnosis of colorectal polyps using convolutional neural networks with visual explanations,’’

Gastroenterology, vol. 158, no. 8, pp. 2169.e8–2179.e8, Jun. 2020, doi: 10.1053/j.gastro.2020.02.036.

[30] S. Mangal, A. Chaurasia, and A. Khajanchi, ‘‘Convolution neural networks for diagnosing colon and lung cancer histopathological images,’’ Sep. 2020, arXiv:2009.03878.

[31] Z. Swiderska-Chadaj, H. Pinckaers, M. van Rijthoven, M. Balkenhol, M. Melnikova, O. Geessink, Q. Manson, G. Litjens, J. van der Laak, and F. Ciompi, ‘‘Convolutional neural networks for lymphocyte detection in immunohistochemically stained whole-slide images,’’ in Proc. MIDL, 2018, pp. 1–12. [Online]. Available: https://openreview. net/forum?id=rk0xLisiM

[32] M. S. Kwak, H. H. Lee, J. M. Yang, J. M. Cha, J. W. Jeon, J. Y. Yoon, and H. I. Kim, ‘‘Deep convolutional neural network-based lymph node metastasis prediction for colon cancer using histopathological images,’’ Frontiers Oncol., vol. 10, p. 3053, Jan. 2021, doi: 10.3389/fonc. 2020.619803.

[33] K. Patel, K. Li, K. Tao, Q. Wang, A. Bansal, A. Rastogi, and G. Wang, ‘‘A comparative study on polyp classification using convolutional neural networks,’’ PLoS ONE, vol. 15, no. 7, Jul. 2020, Art. no. e0236452, doi: 10.1371/journal.pone.0236452. [34] E. Ribeiro, A. Uhl, and M. Hafner, ‘‘Colonic polyp classification with convolutional neural networks,’’ in Proc. IEEE 29th Int. Symp. Comput.-Based Med. Syst. (CBMS), Jun. 2016, pp. 253–258, doi: 10.1109/CBMS. 2016.39.

[35] Z.-Z. Xue, Y. Wu, Q.-Z. Gao, L. Zhao, and Y.-Y. Xu, ‘‘Automated classification of protein subcellular localization in immunohistochemistry images to reveal biomarkers in colon cancer,’’ BMC Bioinf., vol. 21, no. 1, pp. 1–15, Sep. 2020, doi: 10.1186/s12859-020-03731-y.

[36] M. Masud, N. Sikder, A. Al Nahid, A. K. Bairagi, and M. A. Alzain, ‘‘A machine learning approach to diagnosing lung and colon cancer using a deep learning-based classification framework,’’ Sensors, vol. 21, no. 3, pp. 1–21, Feb. 2021, doi: 10.3390/s21030748.

[37] B. S. H. Shabbeer, S. Ghosh, K. K. Babu, S. R. Dubey, V. Pulabaigari, and S. Mukherjee, ‘‘RCCNet: An efficient convolutional neural network for histological routine colon cancer nuclei classification,’’ in Proc. 15th Int. Conf. Control, Automat., Robot. Vis. (ICARCV), 2018, pp. 1222–1227.

[38] K. Sirinukunwattana, S. E. A. Raza, Y.-W. Tsang, D. R. J. Snead, I. A. Cree, and N. M. Rajpoot, ‘‘Locality sensitive deep learning for detection and classification of nuclei in routine colon cancer histology images,’’ IEEE Trans. Med. Imag., vol. 35, no. 5, pp. 1196–1206, May 2016, doi: 10.1109/TMI.2016.2525803.

[39] F. Lippoldt, ‘‘Efficient colon cancer grading with graph neural networks,’’ Oct. 2020, arXiv:2010.01091.

[40] S. Argov, J. Ramesh, A. Salman, I. Sinelnikov, J. Goldstein, H. Guterman, and S. Mordechai, ‘‘Diagnostic potential of Fourier-transform infrared microspectroscopy and advanced computational methods in colon cancer patients,’’ J. Biomed. Opt., vol. 7, no. 2, p. 248, 2002, doi: 10.1117/1.1463051.

[41] D. G. Ward, N. Suggett, Y. Cheng, W. Wei, H. Johnson, L. J. Billingham, T. Ismail, M. J. O. Wakelam, P. J. Johnson, and A. Martin, ‘‘Identification of serum biomarkers for colon cancer by proteomic analysis,’’ Brit. J. Cancer, vol. 94, no. 12, pp. 1898–1905, Jun. 2006, doi: 10.1038/sj.bjc.6603188.

[42] L. Brunese, F. Mercaldo, A. Reginelli, and A. Santone. Neural Networks for Lung Cancer Detection through Radiomic Features. Accessed: Jun. 2021. [Online]. Available:
https://www.cancercenter.com/lungcancer/stages/

[43] H. B. Burke, P. H. Goodman, D. B. Rosen, D. E. Henson, J. N. Weinstein, F. E. Harrell, J. R. Marks, D. P. Winchester, and D. G. Bostwick, ‘‘Artificial neural networks improve the accuracy of cancer survival prediction,’’ Cancer, vol. 79, no. 4, pp. 857–862, Feb. 1997.

[44] H. Chen, H. Zhao, J. Shen, R. Zhou, and Q. Zhou, ‘‘Supervised machine learning model for high dimensional gene data in colon cancer detection,’’ in Proc. IEEE Int. Congr. Big Data, Jun. 2015, pp. 134–141, doi: 10.1109/BigDataCongress.2015.28.

[45] E.-H. Dulf, M. Bledea, T. Mocan, and L. Mocan, ‘‘Automatic detection of colorectal polyps using transfer learning,’’ Sensors, vol. 21, no. 17, p. 5704, Aug. 2021, doi: 10.3390/s21175704.

[46] P. M. Shakeel, A. Tolba, Z. Al-Makhadmeh, and M. M. Jaber, ‘‘Automatic detection of lung cancer from biomedical data set using discrete AdaBoost optimized ensemble learning generalized neural networks,’’ Neural Comput. Appl., vol. 32, no. 3, pp. 777–790, Feb. 2020, doi: 10.1007/s00521- 018-03972-2.

[47] P. Mohamed Shakeel, M. I. Desa, and M. A. Burhanuddin, ‘‘Improved watershed histogram thresholding with probabilistic neural networks for lung cancer diagnosis for CBMIR systems,’’ Multimedia Tools Appl., vol. 79, nos. 23–24, pp. 17115–17133, Jun. 2020, doi: 10.1007/s11042- 019-7662-9.

[48] O. Er, N. Yumusak, and F. Temurtas, ‘‘Chest diseases diagnosis using artificial neural networks,’’ Expert Syst. Appl., vol. 37, no. 12, pp. 7648–7655, Dec. 2010, doi: 10.1016/j.eswa.2010.04.078.

[49] J. Kuruvilla and K. Gunavathi, ‘‘Lung cancer classification using neural networks for CT images,’’ Comput. Methods Programs Biomed., vol. 113, no. 1, pp. 202–209, Jan. 2014, doi: 10.1016/j.cmpb.2013.10.011.

[50] R. Arulmurugan and H. Anandakumar, ‘‘Early detection of lung cancer using wavelet feature descriptor and feed forward back propagation neural networks classifier,’’ in Computational Vision and Bio Inspired Computing (Lecture Notes in Computational Vision and Biomechanics), vol. 28. Cham, Switzerland: Springer, 2018, pp. 103–110, doi: 10.1007/978-3-319- 71767-8_9.