Automated Diagnosis of Gastric Cancer Through VGG16 Convolutional Neural Networks

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Abstract. Stomach cancer remains among the leading causes of mortality, this is why its early detection is another need for a new cancer diagnostic test. This paper illustrates design a CNN-based model for predicting gastric cancer. Specifically, the GASHissDB which is an open access image database with normal and abnormal gastric tissue images was used for this work. Some changes made in the input images included normalization and converting the images to tensors with reference to the enhancement of the model. Fine-tuned five CNN architectures: For feature extractors, used VGG16, ResNet30 and ResNet50 were used to extract features from the images for binary classification tasks. MobileNet-v2 used a different classifier head where the last dropout layer was removed and replaced by fully connected layers to produce probabilities by using the sigmoid function of Keras. The selected performance measures used to benchmark the models were accuracy, precision, recall or sensitivity, and F1-score. Real-time screen interaction was implemented in Streamlit for image classification in addition to probability scoring. The suggested approach possed high accuracy and depended on the chosen indexes which can be a potential applicative tool for clinicians in diagnosis of Gastric cancer. This research also backs the trend where pre-trained CNNs can be utilized in the classification of medical images and throws light into the integration of AI with the clinical related setting.

Keywords: Gastric cancer, pathology, survival prediction, machine learning, Convolutional Neural Networks (CNN), ResNet-50, tissue classification.

1 Introduction

Gastric cancer is one of the most common neoplasms and a dangerous factor for human life Nowadays, gastric cancer is a great problem in early diagnosis stages and adequate therapy. Knowing gastric cancer as early as possible is crucial for increasing chances of successful treatment; however, endoscopic examination, cyto-histological testing, and bioluminescence imaging diagnostics are invasive and time-consuming and are based on the endoscopist's decisions. In recent years, great development in artificial intelligence (AI) and deep learning have suggested that in the future, entire medical imaging could be performed automatically, with a very high diagnostic accuracy.

Another well-liked type that enjoys robust performance in medical images and recognition as well as classification is Convolutional Neural Networks (CNNs). The usage of pre-trained CNN architecture allows its creators to save time on the training of the CNN from scratch to work on

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the overwhelmingly large amount of data, and also to raise the result on an unapplied set of the limited set of the restricted problems of the selected domain. In the present work, propose a CNN framework for the Gastric cancer detection through Finetuning of CNNs on GASHissDB.

This dataset comprises of Normal/Abnormal images where normal mean organ Stomach whereas abnormal have cancer. Just as the beginning of the proposed analytical framework, created a binary classifier from state of art CNN architectures, including VGG 16, ResNet 30, ResNet50. These models were modified by replacing their classifier head with new fully connected layers, which turn out to be more appropriate for binary classification. Because of the function of data preprocessing, normalization process and systematic split up of datasets, our system was built quite strong and general for every dataset.

While evaluating the proposed models, accuracy, precision, recall and the F1 score were ascertained. In addition, a real-time diagnostic system was developed using Streamlit where the user can upload gastric images that are malignant or benign and probability score. This interface can bridge the gap between deploying DL technology independent of clinical diagnosis in gastric cancer and providing readily usable and efficient approaches to clinicians to diagnose the disease.

Advancement in deep learning empowers the healthcare system in the diagnosis accuracy and speed is defined and explained in this paper. Our system aims at early and accurate diagnosis of Gastric cancer and potentially minimizes real work load of the health care professionals entailed in this process.

2 Literature Survey

Describe the proposed gastric histopathological image database, namely, GasHisSDB, which consists of 245,196 images to achieve the best diagnosis of gastric cancer. This will go on to show how both CNNs and ViT in details present a better image classification outcome than with the regular approach [1].

The various type of gastric diseases through gastroscopy images have been improved by the new generation deep learning. Therefore, DenseNet is more accurate compared with other models such as VGG16, SSD and other methods used for improving data set quality and diagnostic performance such as data augmenting, preprocessing, GANs etc. [2]

The study introduces a computer-aided diagnosis (CADx) system using a Vision Transformer and a novel Multi-Filter Auto Augment (MFAA) technique, achieving impressive accuracy in classifying early gastric cancer (F1-score: 0.92, AUC: 0.97). The present study also demonstrates in which way MFAA might assist to attain an even higher level of accuracy in terms of a comparatively small amount of medical data and suggests that the applicability of MFAA is not limited to the selected area of the study [4]. In this regard, the present study puts forward an Early Gastric Cancer Detection (EGCD) model based on enhancing YOLOv4 through E-YOLO and CBAM to better focus on cancerous features while preserving the texture features crucial for cancer detection. An average precision of 94.16 % is achieved pointing up the model's perspective for the assistance of early diagnosis and treatment [5].

CT texture analysis may therefore be helpful as a non-invasive biomarker of sensitivity to chemotherapy, and in classifying gastric cancer as Lauren depending on intratumoral heterogeneity. Despite the key advancements to definitive updates in diagnosis and the treatment the current study has some features of limitation including, study design being only retrospective, a detailed study area and therefore, more study has to be done [6].

The researchers on gastric cancer using data of 1,591 patients divided them into three subclasses based on 14 clinical characteristics. Examination of mesothelioma tumors revealed Gender and Her-1 protein expression as the discriminator; however, evidencing the value of systems biology approach in the development of improved cancer taxonomy and therapy [7]. In particular, this paper calls for the strategy of leveraging features of trained datasets on colorectal cancer for direct detection of gastric cancer using the YOLOv4 model directly. Therefore, the method improves sensitivity and positive predictive value when applied to gastric cancer using another set of gastric cancer dataset for model tuning [8]. Prescribed in the paper is the new invention, entitled the Multi-Focal Cancer Detection Process (MCDP), intended to enhance the process of cancer recognition in concordance with the multimodal optimization as well as the recently developed niche genetic algorithm. They also describe new paradigms of this technology for her employment in the detection of blood, including VEGF based sensors for blood-based detection and how protein-protein interaction data to be incorporated for detection of the cancer related genes besides discussing various problems afflicting diagnosis of stomach cancer [9].

To improve the differentiation degree assessment in pathological images, a Mask Attention R-CNN technique for detecting instance segmentation of gastric cancer cells is presented in this paper. Moreover, the convolutional model proposed outperforms the current approaches such hence, there is high likelihood to assist pathologists in the right diagnosis of gastric cancer and subsequent treatment [10]. The paper also considers the possibility of using microRNAs (miRNAs) particularly as the bio markers for the initial stages of gastric cancer and their roles in the regulation of genes and cancer advancement. This is an implication that through Blood tests aimed at specific miRNAs could increase early detection that seems to have some drawbacks as compared to other methods [11]. The paper introduces the MF-DETR model, which is modified DETR model for early gastric cancer detection; it enhances the probability of detecting small objects in high-resolution endoscopy images. The dog's classification shows 97.79 % of AP for accuracy of the AP50, precision was 92.31% and recalls was 93.91 %, which suggest that this may be the reason for better clinical performance [12].

This paper also develops MIFNET, the deep learning algorithm which is Multi-task Net, Fusion Net, and Global Net to improve the diagnosis result of gastric cancer in this study. It has been believed effective in reducing diagnostic errors and enabling the screening at an early stage, however, they have to be proven clinically by medical professionals [13]. The topics include an AI based image recognition algorithm CNN for diagnosing early gastric cancer and the accuracy introduced by narrow band imaging technology. They reduce mistakes, enhance diagnostics' speed, and, in general, improve clients' outcomes [14]. In this paper, the authors use transfer learning in conjunction with deep CNN to classify M-NBI images for the diagnosis of early gastric cancer, and achieved high accuracy of 98.5%, sensitivity of 98.1%, and specificity of 98.9%. However, it also reveals that customization of existing models, VGG16, InceptionV3, InceptionResNetV2 would improve diagnostic results [15].

3 Methodology

3.1 System Architecture

The current choice of system architecture for the gastric cancer detection project, outlined in Fig 1, is to include multiple interacting components that enable accurate classification of gastric tissue based solely on its image into two categories: Normal and Abnormal. The process begins with the input dataset, GASHissDB, which comprises labeled images stored in two categories: Normal and Abnormal. These images are feed to the Data Preprocessing module that scale intensities of pixels according to mean and standard deviation from the dataset suggested by NVIDIA. The images are then converted into tensors so they will be compatible with deep learning computing environments and optionally increase image data variety by using operations such as flipping and rotation of an image to improve the model's prediction.

Following preprocessing, the dataset is divided into three subsets: In this paper, as the principal of this paper, Divided the data into three splits which include 40% training set for building of the CNN models 30% for validation in terms of hyperparameters tuning and the remaining 30% is used for model evaluation. In the Model Training module in addition to the base CNN models, Train VGG16, ResNet30, and ResNet50 models which are pretrained specifically for binary classification. The classifier heads of these models are replaced by a targeted architecture intending on a fully connected layer with 2048 neurons that uses ReLU as an activation function; second, a dropout layer with a dropout rate of 0.2; lastly, a sigmoid layer to estimate the probability of the two classes.

After that they are tested in the Model Evaluation module with the help of accuracy, precision, recall, as well as F1-score. This step exposes the model to new unseen data so as improve its performance when applied to new unseen data. Last but not the least, Implement the best performing model using a Streamlit Interface, which acts as a smooth user interface to get real-time predictions. Through this interface, new images can be uploaded whereby these images are subjected to the transformations which the authors used during training. The deployed model in the current method classifies the uploaded image as Normal or Abnormal tissue and displays the probability of the decision. This architecture allows operation from inputting the dataset data and reach the real-time prediction feature making it to be appropriate in clinical and research practice for gastric cancer detection.

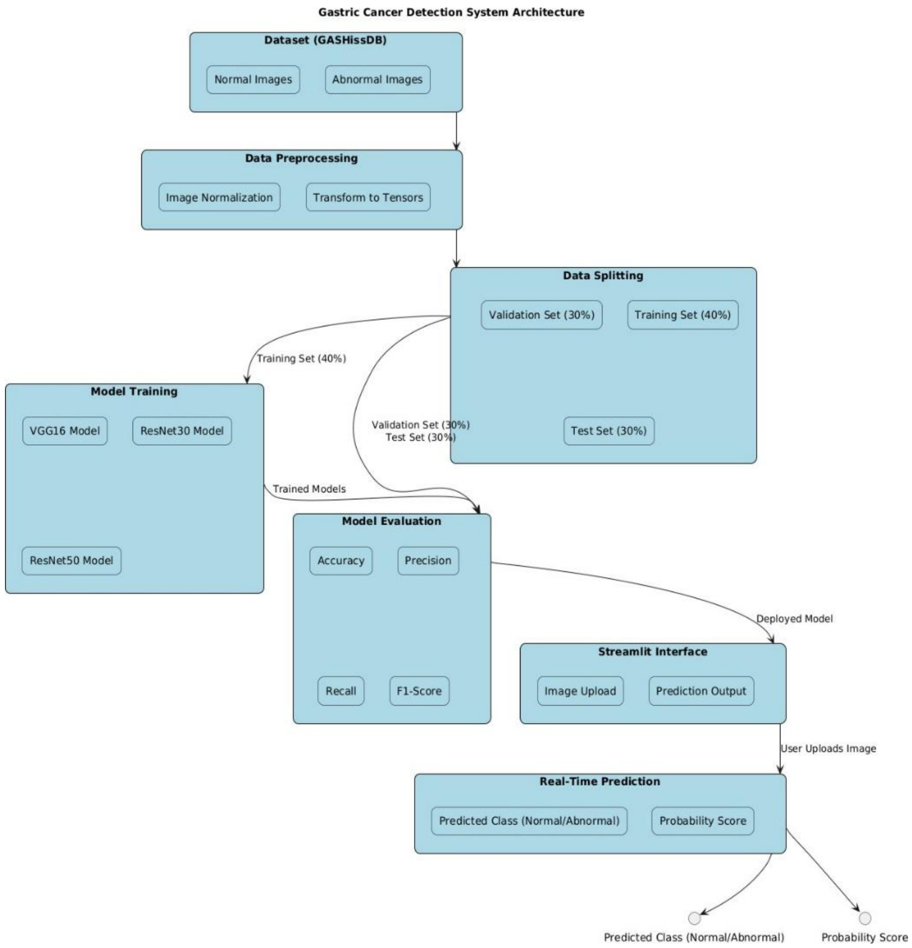

Fig. 1. System Architecture Diagram.

3.2 Database Preparation

The dataset used in this study is the publicly available GASHissDB, which consists of images categorized into two classes: Normal and Abnormal. In order to prepare this dataset for training and evaluation some extra steps were taken. To begin with, the images were rescaled to fit a standard size and encoded into tensors which can be feed into deep learning libraries such as pytorch. Furthermore, each image was normalized with subsequent scaling in which pixel intensities were normalized based on the dataset mean and standard deviation. This normalization step contributed to the improvement of the convergence rate an increase in the stability of the system. Furthermore, the dataset was split into three subsets: Dividing the data set further into three equal parts, the data set was segregated into a training set (40%), a validation set (30%), and a test set (30%), under the condition that training, validation, as well as testing of the models could be carried out separately.

3.3 Dataset Description

The GASHissDB dataset presents analyzed gastric tissue images belonging to two basic segments: Normal and Abnormal. The Normal class contains images of the healthy gastric mucous membrane but the Abnormal class presents images that display the presence of gastric cancer. This experimental data set consists of 1200 tissue sample images obtained from stomach biopsies and these scans have high image resolution suitable for medical image classification applications. The collection of images contains both microscopic tissue alterations as well as enlarged inflammation areas to provide deep learning with varied cases that might need pathology assistance. Fig 2 Shows the Dataset Description Diagram.

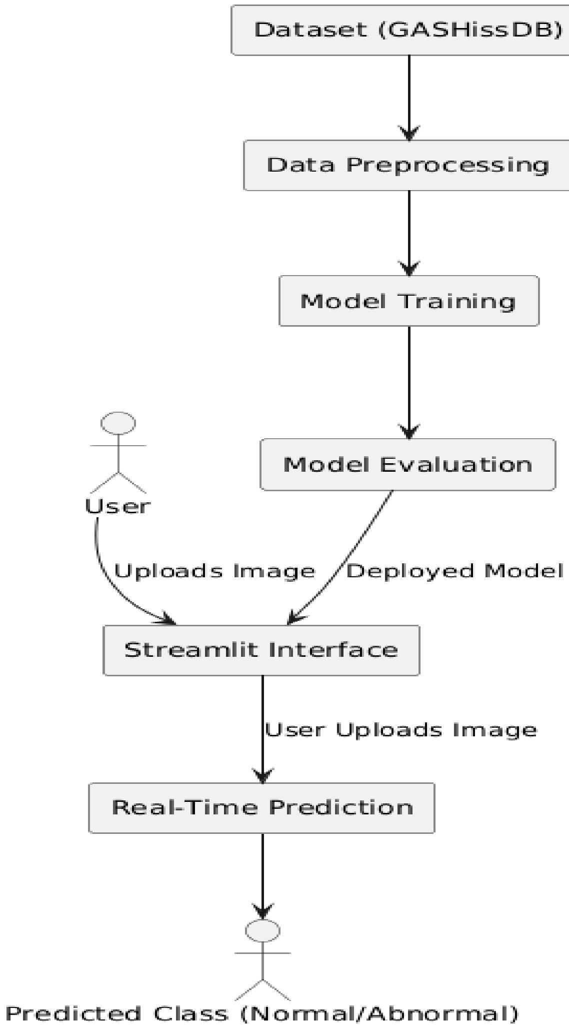

Fig. 2. Dataset Description Diagram.

3.4 Methods of Feature Extraction

The research employed pre-trained CNN models including VGG16 as well as ResNet30 and ResNet50 for extracting features before the FDA-based classification approach. The models extract multi resolution features through different levels of abstraction as they were improved through large-scale datasets such as ImageNet. All pre-trained models maintained their frozen convolutional layers yet trained exclusively their classifier layers to preserve their pre-trained feature-learning capabilities. The learned models provide summarized deep features pertaining to image texture and edge and shape characteristics that serve as required elements for accurate normal and abnormal gastric tissue identification.

3.5 Methods of Classification

For instance, in the classification task that was performed on the pre-trained models, the fully connected layers of the models have been replaced by new classifier heads appropriate for binary classification. This classifier head consisted of a fully connected layer with 2048 neurons to add non-linearity using ReLU. To reduce over-fitting a dropout layer with a dropout rate of 0.2 was added into the model. Finally, the output layer included one neuron, which also used a sigmoid activation function to conform training results to a probability score of the input image belonging or not to Abnormal class. The model was trained using a loss function of binary cross-entropy, while the chosen optimizer was Adam, with a learning rate. This classification architecture enables the model to make accurate predictions from the deep feature learned from the images.

4 Result and Analysis

This evaluation derives from results obtained while training VGG16 and ResNet30 and ResNet50 deep learning models for gastric cancer identification purposes. Out of the three models VGG16 delivered the peak performance with 89.84% accuracy thus becoming the most accurate model. Training for 826 seconds at the 10th epoch marked the best performance period when this model delivered its results. The model demanded the least amount of training time compared to its counterparts. ResNet30 achieved its best accuracy rate of 87.09% during the 8th epoch though its overall accuracy matched VGG16 at 87.09%. Training VGG16 took 903 seconds which demonstrated efficient performance although it was somewhat longer than ResNet50 yet faster than VGG16. The deep architecture of ResNet50 produced only 82.17% accuracy during testing and needed 954 seconds of training time although it had the equivalent number of parameters as other models. ResNet50 demonstrated subpar performance in this particular task because its complex structure and the selected dataset combination led to inferior results although its deeper architecture could prove useful in some applications. The study found VGG16 provided optimal results as a balanced model because it achieved high accuracy while requiring efficient training time which made it suitable for gastric cancer detection. Model Comparison with Training Time and Accuracy Shown in Table 1.

Table 1. Model Comparison with Training Time and Accuracy.

Attribute	VGG16	ResNet30	ResNet50
Epochs	10	8	10
Model Size (Parameters)	675	583	556
Best Epoch	10	8	10
Training Time (Seconds)	826	903	954
Accuracy (%)	89.84	87.09	82.17

5 Conclusions

This research implements a convolutional neural network (CNN)-based system that optimizes gastric cancer detection through analysis of data found in the GASHissDB dataset. The proposed system reaches high accuracy rates in gastric tissue image classification thanks to its advanced pre-trained VGG16 and ResNet50 model fine-tuning process. Advanced feature extraction combined with optimized classifiers through deep learning proved its value in medical diagnostic systems. Medical teams can classify images in real time using the interface which brings artificial intelligence capabilities closer to actual health care implementations. Through its implementation this system demonstrates potential to help medical staff achieve precise diagnoses while decreasing diagnostic times as well as improving healthcare delivery to patients. Subsequent research will concentrate on both enlarging the medical imaging dataset and making the model more advanced to process intricate medical imaging assignments.

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