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Deep Learning based Automatic Detection of Intestinal Hemorrhage Using Wireless Capsule Endoscopy Images

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Abstract. The development of computer-aided diagnosis (CAD) systems for detecting GI bleeding in Wireless Capsule Endoscopy (WCE) image videos has become a hot topic in science, with the goal of reducing physician workload. Due to their constrained feature representation capacity, existing methods provide inadequate precision for bleeding detection. CNN is efficient and a generalised robust system is created using attribute selection and ensemble learning. A supervised learning ensemble will be built in this paper to detect the bleeding in WCE images. With this model, the best possible combination of attributes needed to identify bleeding symptoms in endoscopy images will be discovered. Both the public and the private datasets are trained and tested in our work and our model produced an accuracy of 95.7% with 97.1% sensitivity and 94.6% specificity.

Keywords: Deep learning, Intestinal Hemorrhage, Wireless Capsule Endoscopy Images, Convolutional Neural Network, classification

1 Introduction

Because of its very high capabilities for the feature extraction and classification capabilities, Convolutional Neural Networks (CNN) have become more opted for a broad range of image processing applications[13-16], which includes Wireless Capsule Endoscopy (WCE). CNNs are a form of deep neural network that is both common and reliable. It's especially useful for recognizing objects, faces, and scenes by looking for patterns in the images. They can learn directly from an image dataset, detecting patterns to identify images and obviating the need for manual feature extraction [18,19]. It's a synthetic neural network that uses nonlinear activation functions and neuron weights determined during the training process to make the image analysis via pattern recognition. This pattern detection property is extremely useful in making CNN the most important algorithm. The foundation is made up of the secret layers which are convolutional layers, which distinguishes it from standard Multilayer Perceptron (MLP). These convolutional layers scan the image for different features and conduct scanning operations on it. They take the data, rework it to make it more succinct, and then send it to the appropriate layers. Compared to existing machine algorithms [14], CNN has become a very effective in the area of classification of images due to their ability to learn highly discriminating features from raw pixel intensities, However, the CNN model's use medical image analysis was limited because of the lack of large amount of annotated information required for training[12]. While image analysis is the most common application of CNN also used for other types of data analysis, such as classification and regression. Wireless Capsule Endoscopy (WCE) is a non-invasive method for visualising the entire digestive tract, including the small bowel[11]. It's often used to look at parts of the small intestine that other endoscopy approaches can't reach. The paper proposes a new CNN-augmented architecture for identifying hidden bleeding cases in wireless capsule endoscopy images. Nonetheless, the proposed approach is general, which can be applied to a variety of image classification tasks.

2 Literature Review

In the paper [1] the images obtained from the capsule endoscopy (CE) from the gastrointestinal tract is used as dataset and deep learning based system is designed to overcome the conventional suspected blood indicator (SBI) with dataset collected from various organizations and the result of AUC the blood content detection of was 0.91. The sensitivity, specificity, and accuracy of the CNN were 86.63%, 80.96%, and 87.89% and that system shows the capability of CNN as alternative of conventional SBI system.

In paper[2],they used machine learning to identifying the patients with upper gastrointestinal bleeding. They developed an algorithm find adverse action in patients with initially illness using machine learning Using prospective observational registry, 1539 out of 3369 consecutive patients were enrolled. Primary outcomes included actions such as mortality, hypotension, and re-bleeding within 7 days. The random forest classifier gives 91% accuracy.

Sharif et al proposed [3] a new approach which combines deep CNN and geometric features. They have identified affected area with contrast-enhanced color features segmentation to the given WCE images and then geometric features are extracted. They combine VGG16 and VGG19 CNN model with the geometric features using Euclidean Fisher Vector. They have applied conditional entropy for feature selection and KNN for classification. They got accuracy as 99.42% and precision rate as 99.51% with their model.

In paper[4],they used new technology device called over-the-scope, which recently obtained technical approval from all over the country. Traditionally, GI bleeding has been managed by endoscope with help of doctors or skilled persons. Holes located in the upper tract and also in the lower tract have been generally identified by surgeons. They got accuracy of 90% with help of support vector machine.

In paper[5] a support vector machine (SVM) algorithm to classify WCE video frames in the case of bleeding and the colour extraction feature is concentrated for which SVM is used for in this paper. The dataset collected as video here and then it is transferred as images with the help GPU workstations. The algorithm mentioned here is based on statistical colour feature analysis and this paper shows the accuracy of 88% with SVM linear algorithm

In paper [6], the authors used capsule endoscopy to inspect the small intestine and identify the small bowel bleeding. They have applied their model with capsule endoscopy diagnosing for identifying small bowel tumors in 8.9% of patients. They have said that their model helps for early treatment and diagnosis of the patient and reduce the mortality.

In paper [7], the authors have built a model for automated hemorrhage detection to diagnose intestinal diseases. The automated detection of hemorrhage images from normal images is a quiet complex problem because the appearance and color gradient looks similar. Their proposed a robust intestinal hemorrhage detection system using CNN and produced the result of F-measure as 92.87%.In paper [8], acute bleeding from the colon is usually less dramatic than upper gastrointestinal hemorrhage. Several reasons might contribute to increased death rate, a severe cause of bleeding and continuous bleeding including age, intestinal swollen, bleeding as a result of a separate process. The bleeding in the intestinal tract classified by capsule endoscopy images dataset and gives the accuracy of 94% using SCG optimizer it helps to early identification and diagnosis of the disease and prevents the death rate.In paper [9], the CNN model was built first from Inception V3 model with transfer learning concept which is trained on ImageNet dataset of the WCE of the intestinal tract. The mid-level image representation is computed which is then fine-tuned with labelled endoscopy images. Additionally, they have also applied data augmentation technique and image resampling operation for increasing the size of the database, hence produced the result of accuracy as 89%.In paper[10], the authors used the method super pixel segmentation method to reduce the computational complexity while maintaining high accuracy[20-23]. The dataset taken from the wireless capsule endoscopy it helps to examine the lower, upper intestinal bowel however the drawback is the dataset need to clarify by the clinical person. Results proved that their method outperforms the state-of-the-art methods importantly in terms of sensitivity, specificity, and accuracy attains almost 92% and it helps to automate the process so no need of manual skills or misjudgment not there and helps to diagnose the patient.

3 Proposed Work

The proposed architecture is shown in Figure 1. The main operations are convolution, pooling, activation function and flattening.

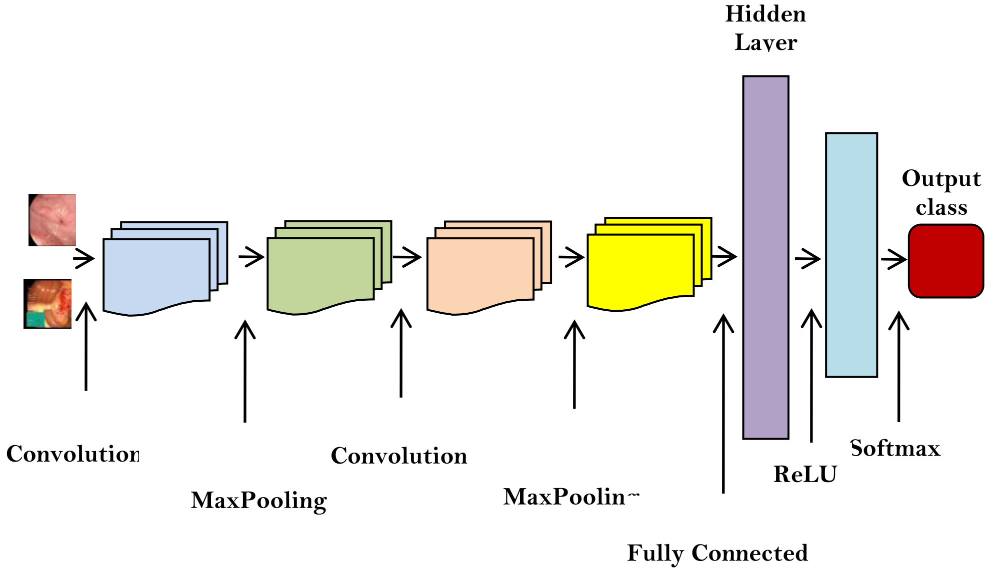

Fig. 2. Pooling (Max pooling and Average Pooling)

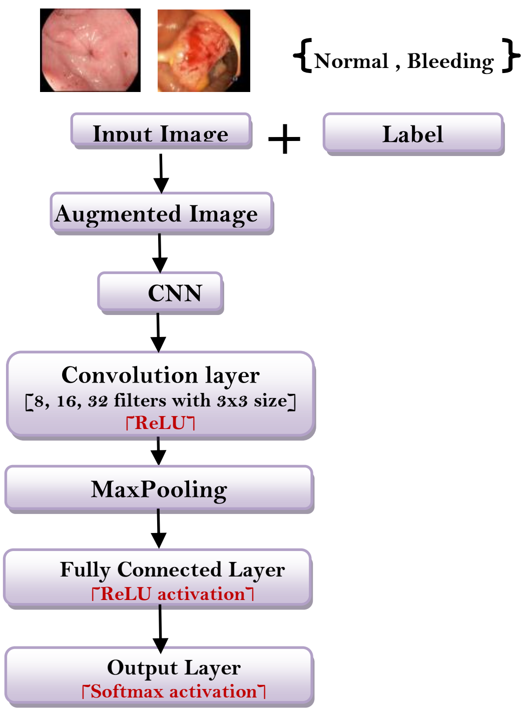

Fig.3. Proposed CNN architecture for bleeding classification

Convolution layer

The convolution layer contains numerous filters used to extract the significant features[15,17] from the given input images. The height and width of the filters are smaller than the input volume of the image. Each filter is manipulated with the input image to determine the feature map made of neurons.

Pooling Layer

Pooling is the process of merging that helps to reduce the data. If the maximum value is taken from the sub-matrix, then it is known as max pooling. If the average values are taken, then it is average pooling. This is clearly shown in Figure 2

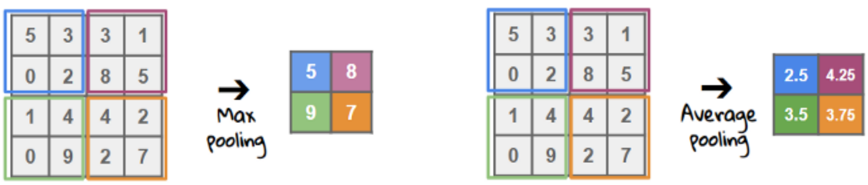

Fig.4. Flow diagram for bleeding classification

Flattening Layer

Flatten layer converts the 2D array data into a 1-dimensional vector which is given as input for the fully connected feed-forward neural network. Flatten the output of the convolutional layers creates a single long feature vector. Using this data, the neural network is trained to identify the different tea leaf diseases.

Rectified Linear Unit(ReLU)

ReLU is one of the popular activation functions used in CNN network. The ReLU will not trigger the activation of all the neurons at the same time in the layer considered. The output of ReLU is zero if the activation of the neuron is negative and that neuron does not get activated further.

Flow Diagram

Fig. 3 represents the flow diagram of the proposed system for the detection of bleeding in GI tract. It consists of different phases namely pre-processing, feature extractions, prediction, and plotting bleeding area for detecting bleeding. The CNN architecture is a layered approach in which the layers are processed sequentially.

Pre-Processing

The images in the dataset are not standardized because it comes from different source. So all the images need to be standardized and fed into the model. To standardize the images, the simple pre-processing technique is used. There are several pre-processing techniques like resizing the images, scaling the images, normalizing the image and dimensionality reduction. The larger image will occupy more space, increases the time complexity and resulting in the large neural network. So, resizing images technique is used to standardize the images. The images are resized as 50 X 50 X 3. The pre-processed images are fed as input to for feature extraction process.

Feature Extraction

The feature of the images can be extracted using Convolutional Neural Network (CNN) architecture. The input image is typically given in a 2D array of neurons which denotes a set of pixels of the image. After pre-processing, the features of the images are extracted using CNN architecture which recognizes and classifies the images. CNN architecture has different layers namely convolution, pooling, and fully connected layer to do the feature extraction. Among these, the convolution layer has different filters to detect the particular feature at every location on the input image. The number of filters used in the convolution layers is mostly 64 or 128 which increment exponentially the number of filters for the layer. The filters divide the input as 2 X 2 with the default stride 1X 1. Each convolution layer embeds an activation function and pooling layer.

Among these, the activation function transforms the weighted sum of input to its higher or lower value like 0 or 1. There are three types of activation function namely binary step function, linear activation function, and non-linear activation function. Among these, non-linear activation functions are used to create multiple layers of neurons to process complex datasets such as images, videos, and audios in order to give high accuracy. Non-linear activation function had different

functions namely sigmoid, hyperbolic tangent, ReLU, leaky ReLU, parametric ReLU, sigmoid, and Swish. Among these, ReLU function is used for all convolution layers because of its computational efficiency than any other activation functions. The output of the activation function is given to the pooling layer helps to reduce only the spatial information, and hence there is only less chance of over-fitting. Moreover, it is a downsampling process that reduces the size of data.

The output from the last convolution layer is fed as the input to the flattening layer. The flattening layer converts the 2D matrix into a vector format. It must be done before entering into the fully connected layer. The first fully connected layer consists of 2048 nodes activated by ReLU activation function. The second layer acts as the output layer. The activation function used in the output layer is sigmoid function and the output from the sigmoid function is a probability ranges between 0 to 1. The label which has the highest probability is assigned as the class of input image. The output layer is defined by several classes to be classified where the number of classes is 2 which include normal class and bleeding class.

4 Dataset Description

The Kvasir dataset is considered consists of a total number of 4778 images. We have used, 70% of the images (3344 images) for training, 30% of the images (1434 images) for testing. The number of images in each class is given in Table 1.

Wireless Capsule Endoscopy (WCE) is a non-invasive procedure for visualizing the entire digestive tract, including the small bowel. It's often used to look at parts of the small intestine that other endoscopy approaches can't reach. The paper proposes a new CNN-augmented architecture for detecting hidden bleeding cases in wireless capsule endoscopy images. Nonetheless, the proposed approach is general and can be applied to a variety of image classification tasks. A WCE video length is 30 minutes is also considered and from that 4000 images are extracted. From that collected set, we have used around nearly 1500 images in our proposed model. Sample images from the dataset are shown in Figure 4 and 5.

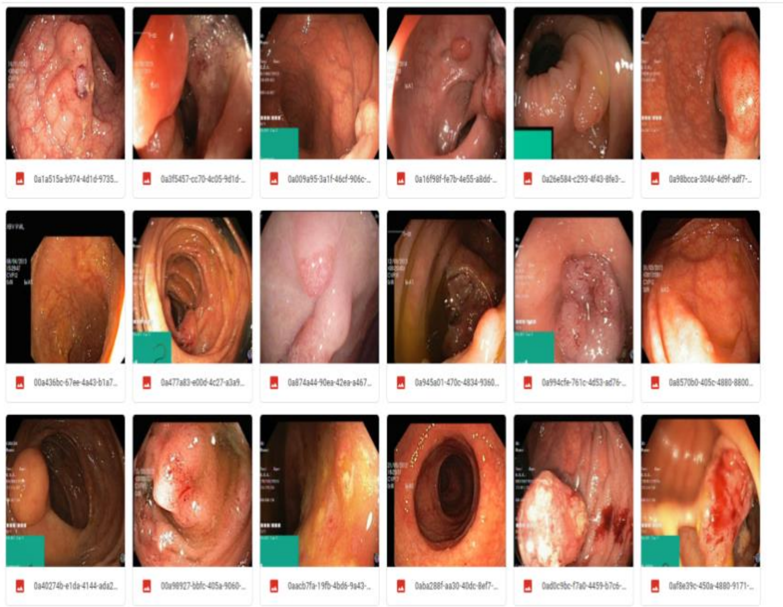

Fig.4. Normal images(sample images)

Fig.5. Bleeding (sample images)

5 Performance Analysis

The various metrics we have considered to evaluate the proposed model are discussed below: These metrics are achieved from the confusion matrix resulted in figure 6. Totally 950 images are used for testing and the confusion matrix shows that the model correctly predicts the class bleeding as 277 and Normal class as 310 the total of 23 images were incorrectly predicted.

5.1 Accuracy

Accuracy is treated as a one of the most important parameters for analyzing the proposed work. The accuracy is the ratio between the summation of true positive(TP) and true negative(TN) to the total number of samples.

$$Accuracy\ (\%) = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Negative + False\ Positive}\ X\ 100 \qquad (1)$$

True Positive (TP): No. of bleeding images are corrected predicted as bleeding
True Negative (TN): No. of normal images are corrected predicted as normal
False Positive (FP): No. of normal images are wrongly predicted as bleeding
False Negative (FN): No. of bleeding images are wrongly predicted as normal

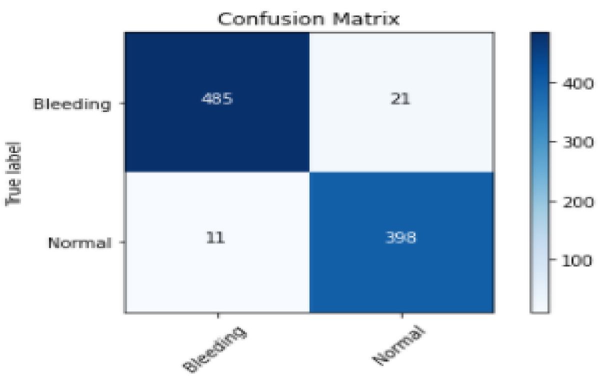

Fig.6. Confusion matrix

5.2 Sensitivity

Sensitivity (SN) is measured as the ratio of number of correctly identified positives (haemorrhage images) to the total number of positives (haemorrhage images). It is also referred as recall (REC) or true positive rate (TPR).

$$Sensitivity\ (\%) = \frac{True\ Positive}{True\ Positive + False\ Positive}\ X\ 100 \qquad (2)$$

5.3 Specificity

Specificity (SP) is calculated as the ratio of number of correctly identified negatives (normal images) to the total number of negatives (normal images). It can also be called as true negative rate (TNR).

$$Specificity\ (\%) = \frac{True\ \ Negative}{True\ Negative + False\ Negative}\ X\ 100 \qquad (3)$$

5.4 Result Discussion

With our model we trained and tested different values of epochs 10, 15 and batch size 16 to 64 with Adam optimizer and the results are given in table 1 and 2.

Table 1. Results achieved for the epoch 10

Metric	Batch size = 16	Batch size = 32	Batch size = 64
Sensitivity	94.2	66.7	96.6

Specificity	96.4	97.0	94.6
Accuracy	95.4	83.3	95.5

Table 2. Results achieved for the epoch 15

Metric	Batch size = 16	Batch size = 32	Batch size = 64
Sensitivity	97.8	97.1	97.6
Specificity	76.2	94.6	85.2
Accuracy	86.0	95.7	90.8

Fig. 7 shows the epoch wise accuracy result. An epoch is one complete pass through the training data. The accuracy increases when increasing the number of epochs. Usually, the training accuracy is continuously improving because the proposed model seeks to find the best fit for the training data which tends to over fit. Epoch value should be chosen in such a way that the model should not over fit.Fig. 8 shows the loss of training and validation gets reducing also denotes the model is good fit.

Fig.8. Accuracy analysis

Fig.9. Loss analysis

6. Conclusion

This work gives an overall review for the techniques of bleeding and normal intestinal tract classification. The ultimate goal of the proposed work is to improve the accuracy of correctly predicting the bleeding intestinal tract portion. Initially, the images are pre-processed. After pre-processing, the features of the images are extracted using either CNN architecture. After feature extraction, the output layer is used to predict the bleeding images. The proposed work has been done with hyper parameter tuning where the different parameters like optimizers, epoch and batch-size are varied. After testing with different optimizers, epoch and batch-size, this model gives the accuracy of 96% while using Adam optimizer for the epoch 10 and the batch size 32. Our model is efficient and it can be an automated system for bleeding classification in GI tract which is highly desired in medical field to overcome medical error, financial and health losses.

This proposed work has some limitations like degrade in accuracy level when the data set have some blurred images, hence the future work is to improve the system which will predict correctly even it has some low quality or blurred images in data sets which are obtained from wireless capsule endoscopy after that it planning to real time use.

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