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BINARY CLASSIFICATION OF ULCERATIVE COLITIS IMAGES USING SUPPORT VECTOR MACHINES (SVMS) WITH THE SQUARE SUM OF SLACK VARIABLES AND SOFTMAX ACTIVATION FUNCTION IN CONVOLUTIONAL NEURAL NETWORKS

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Abstract:

Ulcerative Colitis (UC) is the prevalence of inflammatory bowel disease in India. It is a chronic disease characterized by periods of time with active inflammation and ulcers in gastrointestinal tract. Several patients with Ulcerative Colitis experience long stretches of inflammation interspersed with flares—periods of active inflammation. The likelihood of developing ulcerative colitis can be influenced by a variety of factors, but the majority can be divided into three categories: biological disposition, environmental exposures, and dysregulated immune reaction. Gastroenterologists use endoscopy and colonoscopy procedures to examine the upper digestive system and inner most lining of the colon visually. However, diagnosis of UC is a difficult task because of its varying traits and variety of patterns.

The goal of this research is to identify Ulcerative Colitis remissions using computational algorithms. For image classification problems, finding the best classifier is more competitive based on high-level deep features of images. In this regard a novel Convolutional Neural Network (CNN) is proposed by using Conv2D and Separable Conv2D classes with SVM Classifier and Softmax activation function for better classification of UC images. Automatic identification and effective learning of prominent features from the UC image is the main intent of utilizing CNN in this research. The proposed approach is compared with existing techniques, the outcome and analysis depict that the research is highly effective.

Keywords: bowel disease, remissions, UC images, CNN Model, SVM Classifier, Conv2D, Separable Conv2D, Softmax activation function.

1. Introduction

The rectum and colon's innermost linings are often the sole places where ulcerative colitis (UC) occurs. A person with ulcerative colitis has a higher chance of getting colon cancer [1]. Some of the symptoms include Diarrhea, often with blood or pus, abdominal pain, cramping and fatigue. Many specialists think autoimmune disease is what that causes UC (when healthy tissue is attacked mistakenly by the immune system). In order to eliminate the infection's source, white blood cells are often released into the blood by the immune system to combat

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infections [2]. They often appear gradually and might include diarrhoea, frequently accompanied by blood or pus, fever, lethargy, anaemia, appetite loss, cramping and discomfort in the abdomen, rectal pain and bleeding, and the urgent necessity to urinate but unable to do so [3].

Examination of the intensity and scope of intestinal inflammation can verify the diagnosis of UC. To begin, a tiny, rigid tube holding a camera is placed into your rectum during an endoscopy or colonoscopy (bottom). Diagnosis of UC with the image without the support of medical expert can be accomplished using image processing approaches [4]. Analysation and the processing of pictures with the assistance of the computers are escalating now a days. [5]. A picture is stated as a variation of brightness from point to point. Pictures are digitized before applying any kind of processing techniques [6]. Digitization is the method of converting discrete array points with values of brightness, gray shades and points of the grid. An element in the digital picture is represented by the pixels or point values. Digital computers process the digital images with the help of algorithms is called Digital Image Processing (DIP) [7]. One of the main intents behind image processing is enriching the appearance of the images. The enrichment in images is attained by amplifying the levels of brightness, contrast, blur and eliminating the noise values. In image processing, picture act as both input and output. In the process of image recognition, image features are retrieved as output from the input image. [8]. Digital Image Processing (DIP) incorporates computer algorithms to process the digital images. Analog image processing permits to use wide range of approaches to process the image and avoids the issues of distortion as well as noise construction in the image. Analog image processing is a sub field of image processing [9]. The significant information from the images is retrieved using the analysis and various techniques are applied to yield improved information from the image[10]. From the analysed images 3D parametric maps are generated and values for the calculation is ultimately user-independent and replicable. Image processing techniques are sophisticated, and it has the tendency to establish automation as feasible [11]. Classification is a supervised learning method used in deep learning and statistics, where the computer programme learns from the input data and then applies that learning to classify fresh observations [12]. Speech recognition, handwriting recognition, biometric identification, document classification, disease classification, etc. are a few real-world examples of classification issues [13].

Neural Networks is gaining interest due to its high potential, it is used in the process of classification and prediction approaches [14]. It is a famous and prominent tool for modelling the data. Neural Network is a self adaptive and non-linear approach. Correlation among the input and target patterns are identified [15]. Neural Network is modelled with the learning behaviour of the human brain. It is used in training the complex data and the fields that generate complex data. Neural Networks have the mapping abilities, and it can relate the input pattern to the related output patterns. Neural Network will learn with the assistance of example and eventually can spot the newly formed untrained objects [16]. Neural Network can predict the new objects with the help of already developed objects and possess the ability to generalize the training. Neural Network has the capability to process the data in parallel, distributed way and with high speed [17]. It is a fault tolerant and strong processing system [18].

An image classification system is expected to produce higher classification rate with minimum pre-processing operations [19]. Motivation behind the current research is to design an image classification system that processes the pixel information in a more meaningful manner and thus aids in accurate classification. The inspiration for the invention of artificial neural network came from the study of human brain neurons, especially the interconnection of neurons through synapses and their learning capabilities. In the context of image classification, a convolutional neural network (CNN) is a kind of feed forward artificial neural network that enables the system to find out or figure out the class to which the input image belongs. The CNN is more popular owing to its ability to consider the image itself as input data and to arrange the features for automatic classification. The present research on image classification aims to provide a better classification system for ulcerative colitis [20].

The remaining of the article is organized as follows the recent techniques about classification of UC is detailed in Section 2, the proposed approach SVM with CNN is illustrated in Section 3, the numerical outcomes are illustrated in Section 4, and the article is concluded with recommendation for future in Section 5.

2. Related Works

An important factor influencing therapy response is the detection of ulcerative colitis (UC) and Crohn's disease (CD), however UC and CD can be challenging to spot in less skilled endoscopists. As a result, the research's goal was to create and evaluate a deep learning diagnostic system that could identify between UC and CD using colonoscopy pictures. UC was examined using a deep learning model built on a deep convolutional neural network (CNN). The proposed method has a 99.1% accuracy rate [21].

A trained CNN model is used in a computer-assisted diagnosis system to predict the histological pictures of patients with UC in real-time, objective diagnosis of endoscopic images. The CNN's accuracy in determining the degree of endoscopic infection in ulcerative colitis patients is 90.15% (95% CI, 89.49%:90.82%). 91.28% of predictions of histological remission were accurate. The CNN model and the biopsy data had a kappa coefficient of 82.56%. The computer-aided diagnosis method can accurately and consistently forecast the remission of histological images and evaluate the inflammation of endoscopic images of patients with ulcerative colitis [22].

In-order to deliver a better resolution evaluation of UC, automatic estimate of the Mayo Endoscopic Subscore (MES) for each frame in an endoscopic film is examined. This research presents a unique semi-supervised based classification approach to estimate frame severity from video labels alone where annotating intensity at the frame-level is very costly and labour-intensive. Using data from clinical trials, this research shows that the models achieve significant agreement with actual labels, comparable to that of medical specialists.These results suggest that our approach might be used as the basis for novel clinical endpoints, based on a more granular scoring system, to more accurately assess the efficacy of UC drugs in clinical trials [23].

The location in the colon (e.g., left colon) and the order in which the images were taken, both of which are frequently associated to individual images in endoscopic image sequences, are newly exploited to create a feasible semi-supervised learning strategy for UC classification in this study. The suggested method uses a disentanglement process with those features to effectively extract the crucial data of UC categorization. Even with a modest number of annotated images, experimental results show that the suggested strategy outperforms various other semi-supervised learning approaches in the classification challenge. The proposed method has a classification accuracy of 84.52% [24].

A deep learning-based end-to-end system that can forecast a binary form of the MES from unprocessed colonoscopy films. In contrast to earlier studies, the proposed method replicates the evaluation carried out by a gastroenterologist in practice, which entails watching the entire colonoscopy video, locating visually informative areas, and calculating an overall MES. The MES ground truth, which is only available at the colon segment level, has been used to train and deploy the proposed deep learning-based system using raw colonoscopies, without manually choosing the frames that determine the UC severity [25].

In the treatment of individuals with UC, endoscopic evaluation is crucial to grade the disease activity accurately, identifying complications like malignancy, and confirming mucosal repair. However, this evaluation is complicated by significant intraspecific and interobserver variance. Artificial intelligence methodologies have recently been presented to provide more impartial, repeatable endoscopic evaluation. Firstly, evaluated the performance of various deep learning based CNNs when applied to a wide range of 8000 annotated endoscopic still pictures. DenseNet121 design produced the best accuracy (87.50%) and Area Under the Curve (AUC) (0.90), as opposed to predicting the majority class (a "no skill" model), which produced 72.02% and 0.50 respectively [26].

From the literature, it is identified that most of the researchers concentrated on deep learning for the automatic and effective diagnosis of UC. The approaches in literature are effective in handling certain sample of images when the image count is increased the attainment of accuracy also decreased. Occurrence of overfitting is a major issue in many CNN, which is rectified using the Support Vector Machine (SVM).

3. Proposed Methodology

Image classification is an important process in digital image analysis. It has become an integral component of many automation systems of medical applications. The aim of the present research is to develop a convolutional neural network for realizing high classification accuracy in image classification. To apply the proposed architecture in medical field to detect the ulcerative colitis. The endoscopy and colonoscopy videos are considered in this research where the frames are acquired from the videos for further processing. The block diagram of the proposed framework is given in Figure 1.

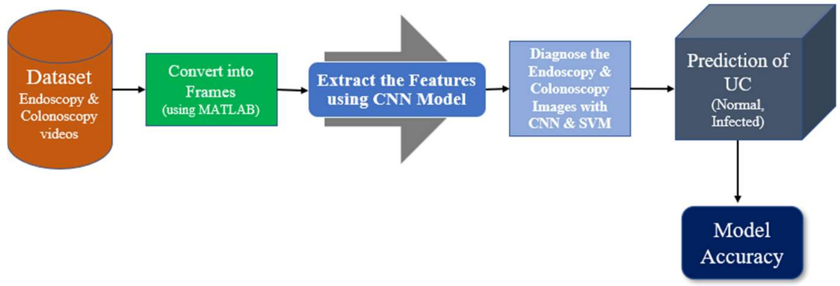

Figure 1. Overall Block Diagram of the Research

The block diagram comprises of frame extraction, feature extraction, classification of UC with CNN & SVM, and performance validation that is illustrated in Figure 1.

Convolutional neural network (CNN or ConvNet) in machine learning is a type of feed forward network that resembles the pattern of visual cortex in animals. The ability of a CNN to capture the spatial pattern in the data makes it best suited for image classification. The convolution operation in mathematics resembles the response of the individual neuron to the stimulus within the receptive field. In a traditional neural network, each layer takes a two-dimensional input whereas in a CNN, each layer is a two dimensional layer. Each layer of the ConvNet converts the input volume to output volume with neuron activations as illustrated in Figure 2.

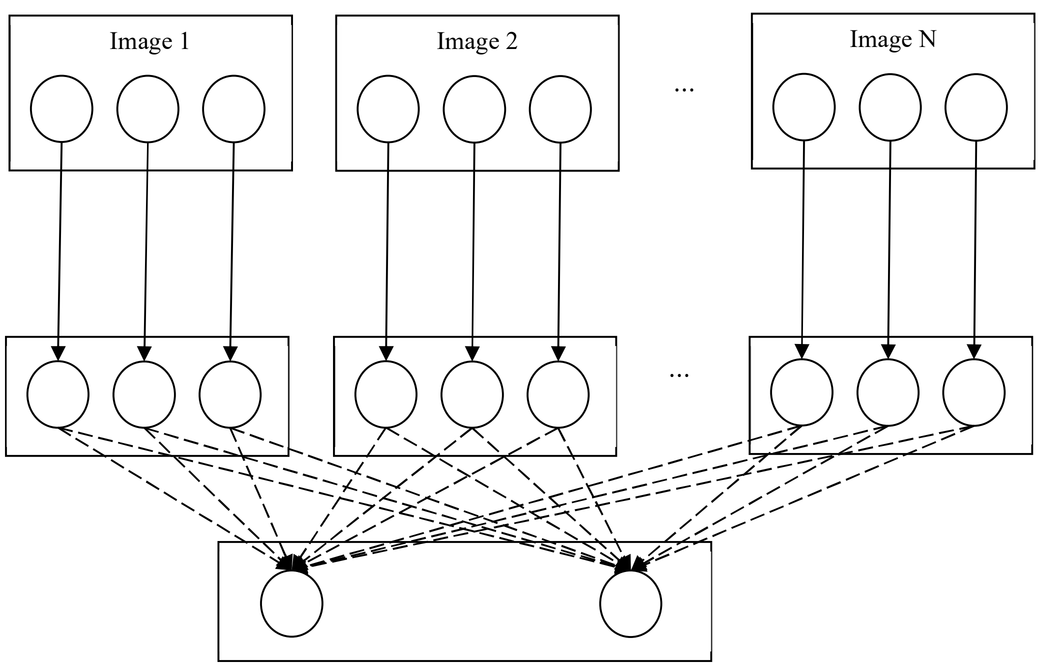

Figure 2. Convolution Neural Network

The structure of CNN is depicted in Figure 2 whereby it considers images for classification and features are retrieved at the feature learning phase. The retrieved significant features are highly effective during learning.

With a view to quickly categorise new data points in the future, the SVM method aims to identify the best line or target variable that can divide n-dimensional space into several classes. The name of this best decision boundary is a hyperplane. A technique to supervised classification is the support vector machine. Every data point is represented graphically in an n-dimensional feature space, where n is the total number of characteristics considered. The data points are classified by employing a hyper plane or decision plane with well-defined gap between the classes. A set of mathematical functions called kernels is used to map the objects and to convert the non-separable problem to separable problem.

SVM employs kernel trick to identify new features for conversion from low dimensional feature space to higher dimensional feature space. In the application of SVM classifier, the parameters should be tuned to reduce the tuning time and to overcome the over-fitting problem. SVM builds a model using a set of labelled training samples and classifies the new samples based on the distance to the hyper plane. Training of the samples is performed by minimizing the error function EF as presented in Equation 1

$$EF = \frac{1}{2}w^T w + c\sum_{i=1}^{N}\varepsilon_i \text{ ---------(1)}$$

with the constraints $y_i(w^T \emptyset(x_i) + b) \geq 1 - \varepsilon_i)\ and\ \varepsilon_i \geq 0, i = 1,2,3,4, \dots \dots \dots N$

C and b are constants; w is the vector of coefficients and ε_i denotes the factor for managing the non-separable input data. Index i is used to label the N training cases. Proper choice of C avoids over-fitting problems.

CNN consists of several layers like convolutional layer, pooling layer, activation function layers, and fully connected layers. Different CNNs have evolved with variations in the dimensions of the input image, number of layers, stacking of layers, and order of layers. Apart from these variations, networks can be tuned by varying the hyper parameters. The most significant advantage of CNN is the number of features generated by it. CNN greatly reduces the effort for feature extraction and feature selection. Unlike traditional neural networks, CNN does not employ the hand-crafted features. Initial convolutional layer extracts edge information present in the input image. The succeeding convolution layer takes out the shape features and the process continue. Some convolution layers result in features that do not convey any meaningful information to the analysts. With increase in the number of convolution layers, it is possible to extract more complicated features from the input images.

In this framework, 2D $conv$ is applied in the $conv$ phases of CNNs for computing the features from the spatial and temporal dimensions. This is carried out by convolving a 2D kernel to the cube created by stacking several neighbour frames. In this formation, the feature maps in the $conv$layer are linked to several neighbor frames in the preceding layer and so the contextual detail is obtained. The cost(v)at point (x, y) on the j^{th} feature map in the i^{th} layer is given by,

$$v_{ij}^{xy} = tanh\left(b_{ij} + \sum_m \sum_{p=0}^{P_i-1} \sum_{q=0}^{Q_i-1} \omega_{ijm}^{pq} v_{(i-1)m}^{(x+p)(y+q)}\right)\text{---------(2)}$$

where R_i denotes the size of the 2D kernel including the temporal dimension, ω_{ijm}^{pq} denotes the $(p, q)^{th}$rate of the kernel linked to the m^{th} feature map in the preceding layer. Based on this 2D $conv$, a 2DCNN is developed for identifying the UC.

Regularization & Fusion

The inputs to 2DCNN are limited to a small number of neighbour slices because of the increased amount of learning parameters while increasing the input window size. In contrast, several features cover many slices. Therefore, it is vital for encoding high-level context details into the 2DCNN frameworks. So, this framework is suggested for capturing the contextual features from a huge number of slices and regularizing the 2DCNN frameworks via these contextual features as secondary outputs.

For all training data, a feature vector is created to encode the long-term lung nodule details. After that, the CNN is encouraged for learning the feature vector nearer to the encoded features by linking the amount of secondary output units to the final hidden layer of CNN and merging the obtained feature vectors on the secondary units during training.

This can support the hidden layer details to be nearer to the high-level contextual feature between slices. Because of the multiple 2DCNN construction, the input is given to each framework in the training phase and the outputs of all frameworks are fused for maximizing the efficiency of 2DCNN frameworks on lung nodule identification.

Convolution Layer

This layer has several filters that glide over the input data, and the summing is calculated using an element-by-element multiplication algorithm. The output value of this layer is therefore estimated to be the input's receptive rate. The weighted summation value is regarded as one of the input elements for the layer below. In the convolutional layer's output, the focus area slides to fill in the other pixel values. Zero padding, stride, and filter size are provided for each operation in the convolution layer. In this approach size of filter is 6, kernel size is 3*3, and uses the similar padding. Further, separable convolution is generated by Separable Conv2D class with filter size 32, kernel size is 3*3, and uses the similar padding.

The Rectified Linear Unit (ReLU) speeds up the convergence of the stochastic descent gradient by acting as an activation function. ReLU is simple to build and uses thresholding, where the value of the activation function is mapped to zero. If the value is negative, it returns zero, and if the value is positive, it returns t. ReLU (AF) is provided as,

$$AF = \max(0, t) \text{ ---------(3)}$$

The gradient method stops learning when the AF value reaches zero and the leaky ReLU is activated in that case. Its function is given as follows,

$$AF_l = \begin{cases} t & t > 0 \\ o \times t & t \leq 0 \end{cases}, o \text{---------(4)}$$

where the predefined parameter is indicated as o and assigned with the value 0.01.

Max Pooling Layer

The most popular pooling technique is max pooling, which slides a nxn window across and down the input with a stride value s, taking the maximum value in the n by n region at each point to minimise the input size. The filter size 'n' and stride size 's' are the two hyperparameters in this layer. This pooling method often leads to overfitting on the training data. To avoid this SVM is incorporated into CNN. The layers are flattened and the 100352 nodes are transmitted to subsequent layer.

Fully Connected Layer

The last pooling layer's flattened output is provided as input to a fully connected layer in this layer. Each neuron from the preceding layer is linked to the layer below it in this layer, which functions like a conventional neural network layer. As a result, there are more parameters in this layer than in the convolution layer. The output layer, which is often a classifier that outputs the probability estimate for the number of classes, is connected to this fully connected layer. In this, hidden layer 1 has 256 nodes, hidden layer 2 has 128 nodes, and hidden layer 3 has 64 nodes.

Softmax Layer

In this layer the classification is performed and the softmax function is exploited in the output layer that is a considered as a normalized exponent value of output information. This indicates the output probability and function is differentiated. Further, the exponential pixel value increases the probability to maximum level. The softmax is equated as,

$$Op_x \frac{e^{z_x}}{\sum_{x=1}^{M} e^{z_x}} \text{---------(5)}$$

where output of the softmax is indicated as op_x for the output count x, z_x is the output x before the softmax, and total count of the output node is indicated as M. The class labels are categorized in this layer.

The overall performance of the algorithm is given in Figure 3.

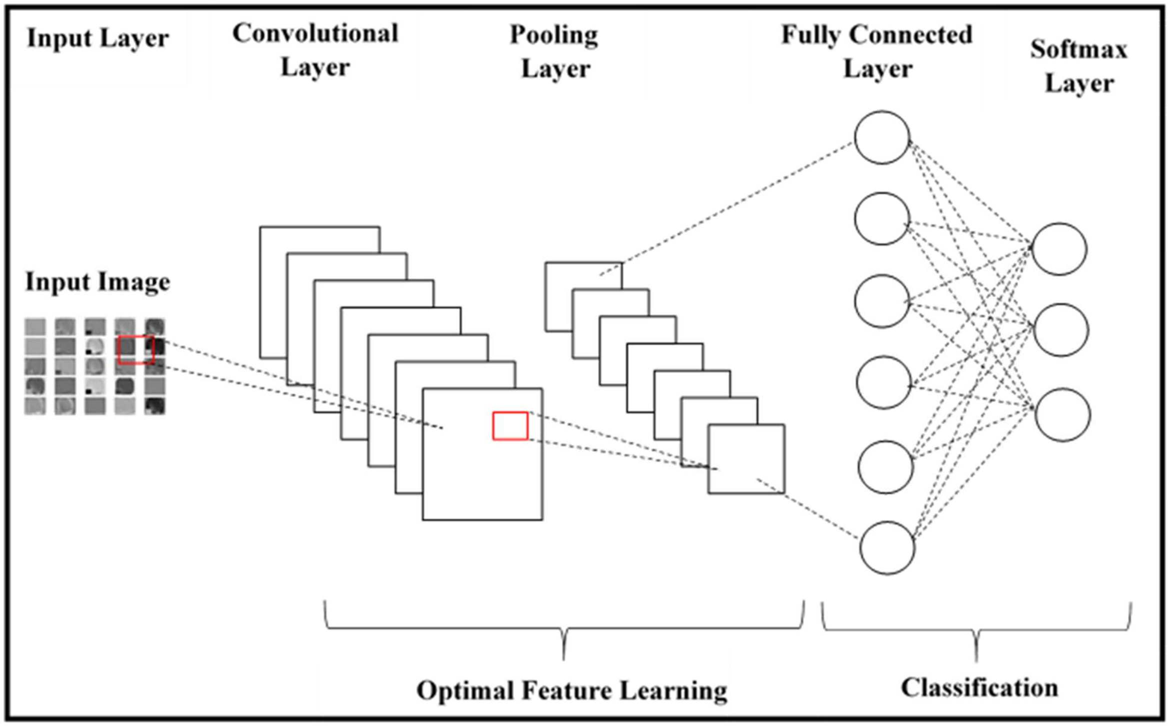

Figure 3. Classification of UC using CNN

4. Result and Discussion

In this research the dataset deployed for implementation is taken from Kaggle [27], which is publicly available. The research is accomplished using python with intel i5 processor, RAM 8 GB, and Widows 10 OS. The description of the dataset is given in Table 1.

Table 1. Dataset Description

S.No	Description of Samples	Platform	# Images	Usage
1	Endoscopy Images of Normal Colon	The Hyper Kvasir Dataset www.kaggle.com	960	Model Selection
2	Endoscopy Images of Infected Colon	The Hyper Kvasir Dataset www.kaggle.com	652	Model Selection
3	Endoscopy Images of Normal Colon	The Hyper Kvasir Dataset www.kaggle.com	370	Model Evaluation
4	Endoscopy Images of Infected Colon	The Hyper Kvasir Dataset www.kaggle.com	338	Model Evaluation

Total number of images considered in this research is 2350 and the infected image count is 1000. The process of training is accomplished using 1612 images and testing is attained using 713. The image acquired from the feature map is given in Figure 4.

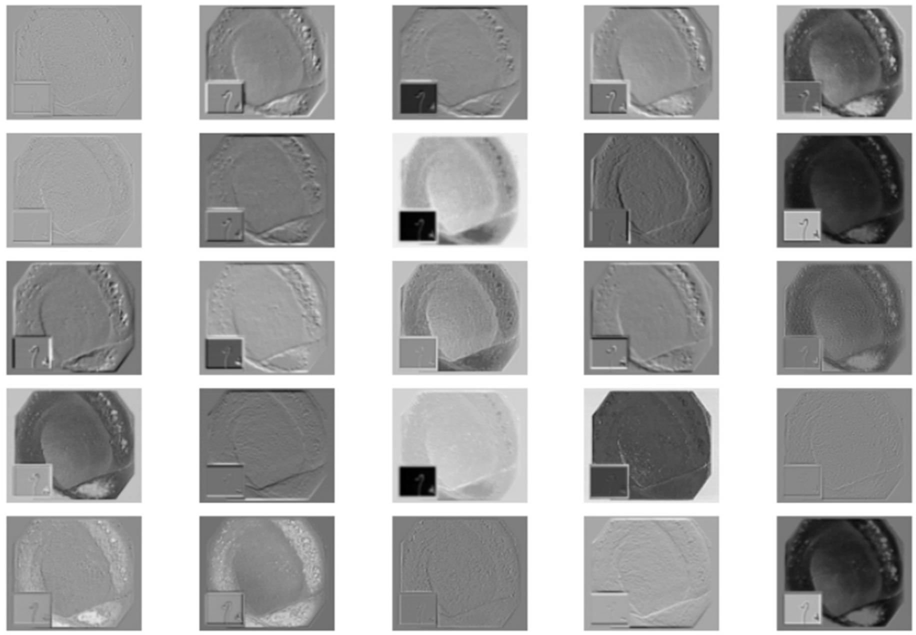

Figure 4. Feature map of UC images

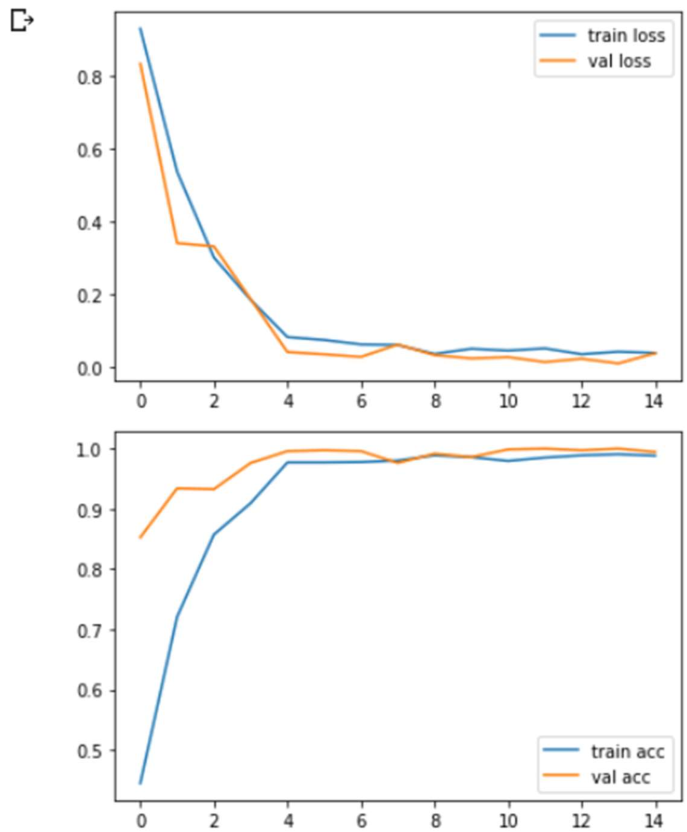

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Figure 5. Comparison of Loss Function and Accuracy

Figure 5 depicts the occurrence of loss or error over the performance of the CNN and the accuracy rate for different iterations . The rate of accuracy increases at the count 2 and loss decreases at count 4. The performance of the CNN is enriched with the decrease of the loss function, whereas an effective classification of UC is achieved. Accuracy is used to measure the performance of the classifier, and the loss function optimizes the performance. For CNN, the loss function decreases as accuracy increases, i.e., the classifier model is efficient as the number increases.

Area Under Curve: An overall measure of performance across all potential classification criteria is provided by AUC. AUC can be seen as the likelihood that the model values a randomly chosen positive example higher than a randomly chosen negative example.

```
14/14 [==============================] - 23s 2s/step - loss: 0.4269 - auc: 0.8793 - val_loss: 0.8513 - val_auc: 0.9313
Epoch 5/20
14/14 [==============================] - 23s 2s/step - loss: 0.4155 - auc: 0.8809 - val_loss: 0.9639 - val_auc: 0.9418
Epoch 6/20
14/14 [==============================] - 23s 2s/step - loss: 0.3590 - auc: 0.9078 - val_loss: 0.9100 - val_auc: 0.9458
Epoch 7/20
14/14 [==============================] - 24s 2s/step - loss: 0.3633 - auc: 0.9024 - val_loss: 0.7310 - val_auc: 0.9515
Epoch 8/20
14/14 [==============================] - 24s 2s/step - loss: 0.3601 - auc: 0.9090 - val_loss: 0.7709 - val_auc: 0.9538
Epoch 9/20
14/14 [==============================] - 23s 2s/step - loss: 0.3946 - auc: 0.8954 - val_loss: 0.6642 - val_auc: 0.9549
Epoch 10/20
14/14 [==============================] - 24s 2s/step - loss: 0.3557 - auc: 0.9137 - val_loss: 0.7561 - val_auc: 0.9620
Epoch 11/20
14/14 [==============================] - 24s 2s/step - loss: 0.3267 - auc: 0.9278 - val_loss: 0.7646 - val_auc: 0.9606
Epoch 12/20
14/14 [==============================] - 24s 2s/step - loss: 0.3827 - auc: 0.9101 - val_loss: 0.6264 - val_auc: 0.9561
Epoch 13/20
14/14 [==============================] - 23s 2s/step - loss: 0.3082 - auc: 0.9340 - val_loss: 0.5287 - val_auc: 0.9560
Epoch 14/20
14/14 [==============================] - 23s 2s/step - loss: 0.2924 - auc: 0.9447 - val_loss: 0.6820 - val_auc: 0.9551
Epoch 15/20
14/14 [==============================] - 23s 2s/step - loss: 0.2812 - auc: 0.9462 - val_loss: 0.6085 - val_auc: 0.9555
Epoch 16/20
14/14 [==============================] - 23s 2s/step - loss: 0.2686 - auc: 0.9532 - val_loss: 0.7764 - val_auc: 0.9654
Epoch 17/20
14/14 [==============================] - 23s 2s/step - loss: 0.2467 - auc: 0.9587 - val_loss: 0.6143 - val_auc: 0.9599
Epoch 18/20
14/14 [==============================] - 23s 2s/step - loss: 0.2593 - auc: 0.9532 - val_loss: 0.8235 - val_auc: 0.9656
Epoch 19/20
14/14 [==============================] - 23s 2s/step - loss: 0.2503 - auc: 0.9575 val_loss: 1.2160 - val_auc: 0.9671
Epoch 20/20
14/14 [==============================] - 23s 2s/step - loss: 0.2719 - auc: 0.9532 val_loss: 0.7954 - val_auc: 0.9581
```

Figure 6. Acquired AUC Values for Diverse Epoch

Accuracy: The number of correctly identified instances divided by the total number of instances provides an approximation of the classification accuracy of the UC image. The accuracy value establishes the categorization model's competence. The true positive (TP) and true negative (TN) numbers obtained from UC classes are used to gauge accuracy. The algorithm with maximum accuracy is termed as effective classification algorithm. The accuracy value is estimated as follows,

$$Accuracy = \frac{True\ Positive\ (TP) + Tr \quad Negative(TN)}{True\ Positive(TP) + True\ Negative(TN) + False\ Positive(FP) + False\ Negative(FN)}$$

Precision: The closeness of the measurement and the relevance among the determined values are indicated by the positive analytical value or precision. The precision is expressed in terms of random errors and is calculated using statistical factors. Precision and accuracy are equivalent concepts in terms of values. The value of precision is often expressed using binary or decimal digits. It is calculated using the True Positive (TP) and False Positive (FP) rates of disease detection. It is calculated as

$$Precision = \frac{TP}{TP + FP}$$

Recall: The percentage of linked occurrences among the actual reclaimed cases is the recall. The recall is an estimation metric for the success rate of a prediction, and it is returned along with the number of related results. It is calculated as,

$$Recall = \frac{TP}{TP + FN}$$

F-measure: F-measure or F-score is described as a test's accuracy in the categorization problem. Precision and recall values are used to calculate the F-measure, where recall is the percentage of linked instances among the actually reclaimed instances and precision is the count of true positive values (positive values or correctly categorised values) (sensitivity or classified instances). The precision value and recall value are provided as a harmonic mean in all other cases. It is computed as,

$$F - measure = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

The performance of the existing and proposed technique is given in Table 2 and the graphical illustration is given in Figure 6.

Table 2. Comparison of Performance

Algorithm	Accuracy	Precision	Recall	F-measure
DNN	0.917431	0.957895	0.947917	0.95288
CNN	0.884956	0.935484	0.925532	0.930481
OGDR	0.869565	0.923913	0.913978	0.918919
CNN+SVM	0.952381	0.979381	0.969388	0.974359

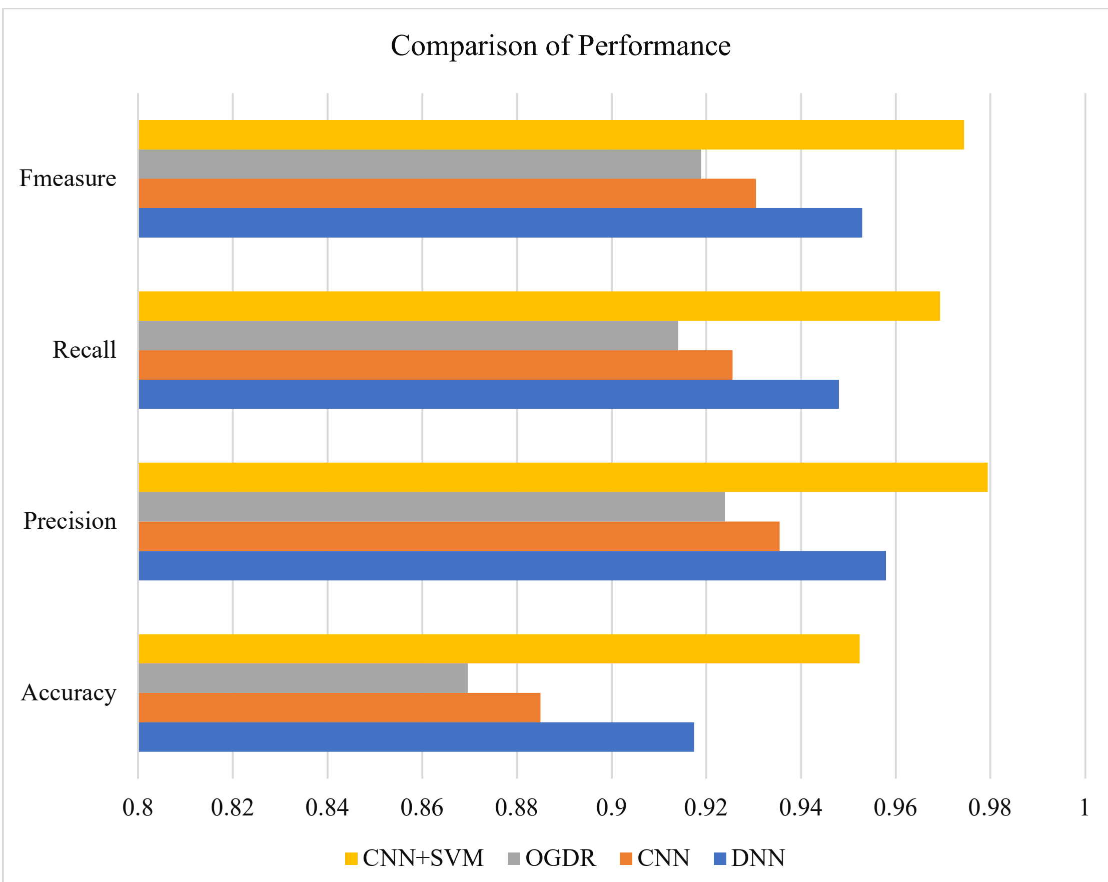

Figure 6. Comparison of Performance

From Figure 6 it is identified that the accuracy of the CNN+SVM is 0.952381 that is higher than {DNN, CNN, and OGDR} of {0.03495, 0.067425, and 0.082816}. From the observation it is identified that the proposed approach is highly effective with the higher rate of classification accuracy. The precision of the CNN+SVM is 0.979381 that is higher than {DNN, CNN, and OGDR} of {0.021487, 0.043898, and 0.055468}. From the observation it is identified that the proposed approach is highly effective where the precision is high. The recall of the CNN+SVM is 0.969388 that is higher than {DNN, CNN, and OGDR} of {0.021471, 0.043856, and 0.055409}. From the observation it is identified that the proposed approach is highly effective where the recall is high. The f-measure of the CNN+SVM is 0.974359 that is higher than {DNN, CNN, and OGDR} of {0.021479, 0.043878, and 0.05544}. From the observation it is identified that the proposed approach is highly effective where the f-measure is high.

5. Conclusion

Enhancing the appearance of the images is one of the key goals of image processing. By boosting the levels of brightness, contrast, blur, and removing the noise values, the enrichment in image is achieved. An overall measure of performance across all potential classification criteria is provided by AUC. Ulcerative colitis is one of the harmful diseases that can be controlled with the support of early diagnosis. The process of diagnosis can be automated, and effectiveness is attained using computation algorithms. In this work, keen pixel extraction of endoscopy images is analyzed, and patient can easily identify the severity of UC and possibilities. The CNN+SVM attained 95% accuracy during the extraction for getting the optimum results. Colon images with different UC stages are classified using Support Vector Machine Classifier. In future, the approach can be extended to apply and compare SVM and ELM classifiers to obtain better results in image classification.

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