GASTRIC CANCER IDENTIFICATION USING DEEP LEARNING

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ABSTRACT

Cancer is one of the diseases involving abnormal cell growth with the potential to invade or spread to other parts of the body. Over 100 types of cancers affect humans, tobacco use is the cause of about 22% of cancer deaths. Among these, gastric cancer causes the second largest deaths all over the world. Manual pathological inspection of gastric slice is time-consuming and usually suffers from inter-observer variations. This paper, proposes a deep learning based framework, namely Gastric Net, for smart gastric cancer identification. The proposed network adopts different architectures for shallow and deep layers for better feature extraction. This evaluates the proposed framework on publicly available BOT gastric slice dataset. The experimental results show that our deep learning framework performs better than state-of-the-art networks like Dense Net, ResNets, and achieved an accuracy of 100% for slice-based classification.

Keywords: **Gastric Cancer, BOT Gastric Slice Dataset, Dense Net, Classification**

I.INTRODUCTION

In the developing world, 15% of cancers are due to infections such as *Helicobacter pylorii*, hepatitis B, hepatitis C, human papillomavirus infection, Epstein–Barr virus and human immunodeficiency virus(HIV). These factors act at least partly, by changing the genes of a cell. Gastric malignant growth is the fourth most generally analyzed disease. Despite the fact that the rate of gastric malignant growth has continuously diminished in the course of the last 50 years, disease at proximal stomach is on the ascent. Today, gastric malignant growth is as yet the seventh most regular reason for disease related demise in the United States and the anticipation of cutting edge gastric malignancy stays poor. Gastric carcinogenesis is a multistep and multifactorial procedure. While the gastric malignant tumor growth in intestine is easy to identify with ecological factors like Helicobacter pylori disease(60% of death), diet and way of life are more frequently connected with hereditary irregularities. [3]There are several symptoms associated with stomach cancer. However there are different existing symptoms which are difficult to diagnose pathologically.

It is for this reason that so many people with stomach cancer are not diagnosed until the disease is already advanced.Earlysymptoms of stomach cancer may include:a sensation of being very full during meals, swallowing difficulties known as dysphagia, feeling bloated after meals, frequent burping, heartburn, indigestion that does not go away, stomachache or pain in the breastbone, trapped wind and vomiting which may contain blood.

Gastric Cancer(GC) is characterized as an aggressive malignancy, which is very tough to be detected at an early stage.GC is defined as a complex, multistep process involving multiple genetic and epigenetic alterations leading to aberrant expression of key regulating factors. Despite a lot of research efforts, GC remains to be the cancer without clear symptoms at onset, poor prognosis, with metastasis and recurrence. The pathological examination is one of the most commonly used diagnosis method for GC, which provides definitive disease diagnoses to guide patient treatment and management decisions. The manual pathological inspection of sentinel lymph nodes is time-consuming and laborious. Over the past several decades there has been increasing interest in developing computational methods to assist in the analysis of microscopic images in pathology. Automatic classification of the pathological image is a very challenging problem.

DISADVANTAGES

- Manual operation is required for the analysis.
- Cancer classification by naked eye might cause human errors

II.LITERATURE SURVEY

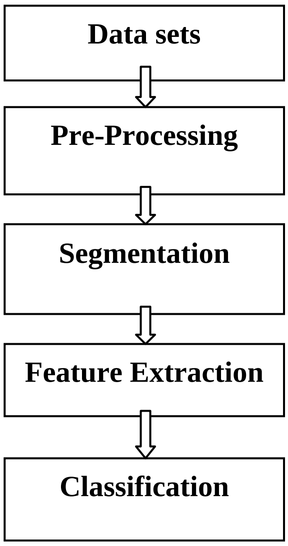
The proposed platform consists of a swallowable capsule[9] connected to external water distribution and vision acquisition systems by a disposable, multi-channel, soft tether. [13] The capsule is first comprised of a disposable outer shell with two fluid suction ports and four fluid exhaust ports. The exhaust ports, placed in 90◦ intervals around the capsule's cylindrical body and oriented at 90◦ relative to the capsule's axial direction, allow the Hydro jet to achieve two-DoF motion when pressurized water is expelled. Through selective activation of the exhaust ports at varying water pressures, the Hydro jet is able to operate in a quasi-hemispherical region. A third DoF can be introduced to the system through the feeding and retraction of the attached multi-channel tether. Suction ports allow the operator to control the amount of fluid within the subject's stomach during a procedure. On the front side of the Hydro jet's outer shell is a viewing window for the internal camera. Connection points for the multi-channel tether are housed in the rear of the capsule [15]. The Hydro jet's inner core module contains the endoscopic camera and LEDs. [5] A four-pole female connector is located on the backside of the inner core. This module rests within a waterproof cavity inside the Hydro jet's outer shell. The inner core module is easily inserted or removed from the Hydro jet's outer shell prior to and following cavity inside the Hydro jet's outer shell. The inner core module is easily inserted or removed from the Hydro jet's outer shell prior to and following a procedure respectively, allowing the on-board electronics to be reclaimed and reused.

III.METHODOLOGY

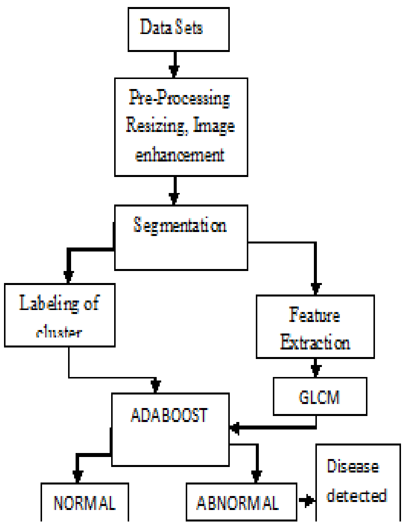
PROPOSED SYSTEM

The disadvantage of existing system is overcome in the proposed system. In this paper, we proposed a patch based deep learning framework for gastric cancer identification.We proposed a network using different structures for shallow and deep layers, and applied it for gastric cancer identification. Experimental results illustrate the excellent classification performance of proposed deep learning network, which outperforms several well-known deep learning frameworks. In this section, we introduce the deep learning network developed for gastric cancer identification. The MATLAB performs the image processing techniques to detect the gastric cancer and provides the result to the microcontroller. The controller updates the result over cloud using IOT module.

PROCESS



BLOCK DIAGRAM



PREPROCESSING

Blurring is used in preprocessing steps, such as removal of small details from an image prior to object extraction and bridging of small gaps in lines or curves. The idea is replacing the value of every pixel in an image by the average of the gray levels in the neighborhood defined by the filter mask. The next step in the process is to segment the lesion from the surrounding skin. Since a clear color distinction existed between lesion and skin, thresholding is very suitable for this task. A black and white image is produced and its size is adjusted in order to include the entire border region in the segmented image.In image analysis, segmentation is the partitioning of a digital image into multiple regions (sets of pixels), it is a process of identifying an object or pattern in the given work space. The process consists of partitioning an image into non-intersecting regions such that each region is homogeneous and the union of no two adjacent regions is homogeneous. The main objective of the digital image segmentation is the partition of an image into mutually exclusive and exhausted region.In pattern recognition and in image processing, feature extraction is a unique form of dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant then the input data will be transformed into a reduced representation set of features.Feature Extraction is not only helpful in identifying the tumorit also helps us to locate where it is exactly located and helps in predicting to the next stage. Transforming the input data into the set of features is called feature extraction

CLASSIFICATION

Classification tasks usually involves separating data into training and tasting sets. Each instances in the training set contains one target value (i.e. the class labels) and several attributes (i.e. the features).

DATA SET

Basically we have three data sets: training, validation and testing.We train the classifier using 'training set', tune the parameters using 'validation set' and then test the performance of your classifier on unseen 'test set'. An important point to note is that during training the classifier only the training and/or validation set is available. The test set must not be used during training the classifier. The test set will only be available during testing the classifier.

There is no one way of choosing the size of training/testing set and people apply heuristics such as 10% testing and 90% training. However, doing so can bias the classification results and the results may not be generalizable. A well accepted method is N-Fold cross validation, in which you randomize the dataset and create N (almost) equal size partitions. Then choose Nth partition for testing and N-1 partitions for training the classifier. Within the training set you can further employ another K-fold cross validation to create a validation set and find the best parameters. And repeat this process N times to get an average of the metric. Since we want to get rid of classifier 'bias' we repeat this above process M times (by randomizing data and splitting into N fold) and take average of the metric. Cross-validation is almost unbiased, but it can also be misused if training and validation set comes from different populations and knowledge from training set is used in the test set.

ADABOOST

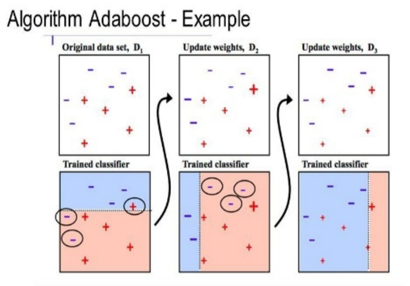
AdaBoost, short for Adaptive Boosting, is a machine learning meta-algorithm formulated by Yoav Freund and Robert Schapire, who won the 2003 Gödel Prize for their work. It can be used in conjunction with many other types of learning algorithms to improve performance. The output of the other learning algorithms ('weak learners') is combined into a weighted sum that represents the final output of the boosted classifier. AdaBoost is adaptive in the sense that subsequent weak learners are tweaked in favor of those AdaBoost is sensitive to noisy data and outliers. In some problems it can be less susceptible to the overfitting problem than other learning algorithms. The individual learners can be weak, but as long as the performance of each one is slightly better than random guessing, the final model can be proven to converge to a strong learner.

Every learning algorithm tends to suit some problem types better than others, and typically has many different parameters and configurations to adjust before it achieves optimal performance on a dataset, AdaBoost (with decision trees as the weak learners) is often referred to as the best out-of-the-box classifier. When used with decision tree learning, information gathered at each stage of the AdaBoost algorithm about the relative 'hardness' of each training sample is fed into the tree growing algorithm such that later trees tend to focus on harder-to-classify examples.

$$F_T(x) = \sum_{t=1}^{T} f_t\,(x)$$

$$E_t = \sum_{t} E[F_{t-1}(x_i) + \alpha_t h(x_i)]$$

Problems in machine learning often suffer from the curse of dimensionality- each sample may consist of a huge number of potential features (for instance, there can be 162,336 Haar features, as used by the Viola–Jones object detection framework, in a 24×24 pixel image window), and evaluating every feature can reduce not only the speed of classifier training and execution, but in fact reduce predictive power, per the Hughes Effect. Unlike neural networks and SVMs, the AdaBoost training process selects only those features known to improve the predictive power of the model, reducing dimensionality and potentially improving execution time as irrelevant features need not be computed.



EARLY TERMINATION

[12] A technique for speeding up processing of boosted classifiers, early termination refers to only testing each potential object with as many layers of the final classifier necessary to meet some confidence threshold, speeding up computation for cases where the class of the object can easily be determined. One such scheme is the object detection framework introduced by Viola and Jones: in an application with significantly more negative samples than positive, a cascade of separate boost classifiers is trained, the output of each stage biased such that some acceptably small fraction of positive samples is mislabeled as negative, and all samples marked as negative after each stage are discarded. If 50% of negative samples are filtered out by each stage, only a very small number of objects would pass through the entire classifier, reducing computation effort. This method has since been generalized, with a formula provided for choosing optimal thresholds at each stage to achieve some desired false positive and false negative rate.

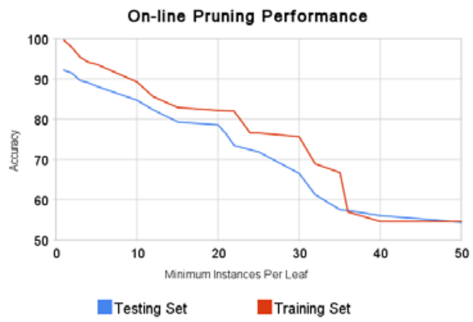
In the field of statistics, where AdaBoost is more commonly applied to problems of moderate dimensionality, early stopping is used as a strategy to reduce overfiting. A validation set of samples is separated from the training set, performance of the classifier on the samples used for training is compared to performance on the validation samples, and training is terminated if performance on the validatio sample is seen to decrease even as performance on the training set continues to improve.

TOTALLY CORRECTIVE ALGORITHM

For steepest descent versions of AdaBoost, where {\displaystyle \alpha _{t}} \alpha_t is chosen at each layer t to minimize test error, the next layer added is said to be maximally independent of layer t: it is unlikely to choose a weak learner t+1 that is similar to learner t. However, there remains the possibility that t+1 produces similar information to some other earlier layer. Totally corrective algorithms, such as LPBoost, optimize the value of every coefficient after each step, such that new layers added are always maximally independent of every previous layer. This can be accomplished by backfitting, linear programming or some other method.

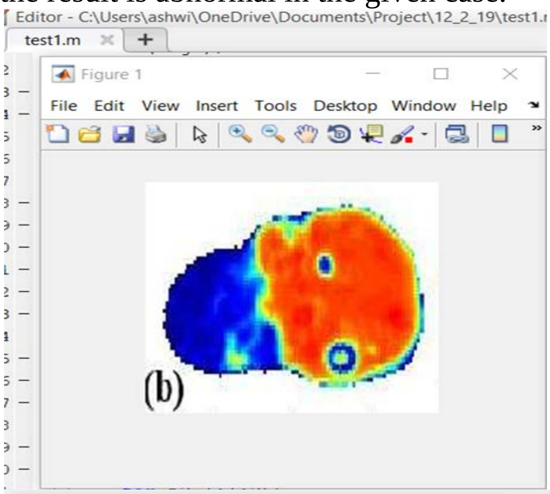
PRUNING

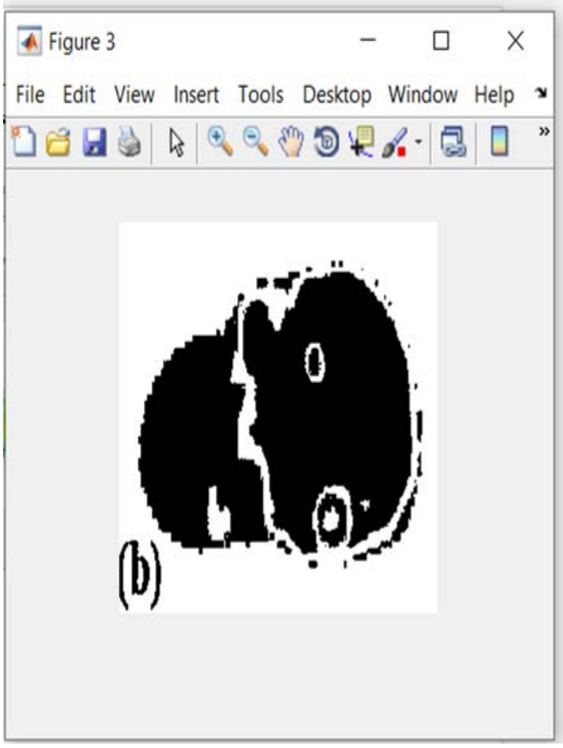
Pruning is the process of removing poorly performing weak classifiers to improve memory and execution-time cost of the boosted classifier. The simplest methods, which can be particularly effective in conjunction with totally corrective training, are weight- or margin-trimming: when the coefficient, or the contribution to the total test error, of some weak classifier falls below a certain threshold, that classifier is dropped. Margineantu & Dietterich suggest an alternative criterion for trimming: weak classifiers should be selected such that the diversity of the ensemble is maximized. If two weak learners produce very similar outputs, efficiency can be improved by removing one of them and increasing the coefficient of the remaining weak learner

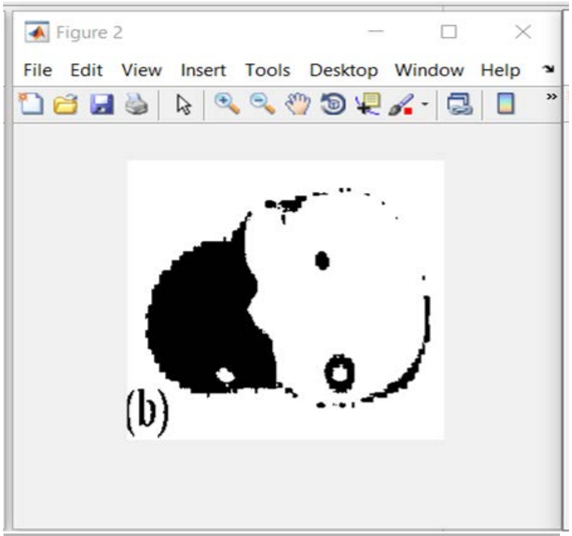


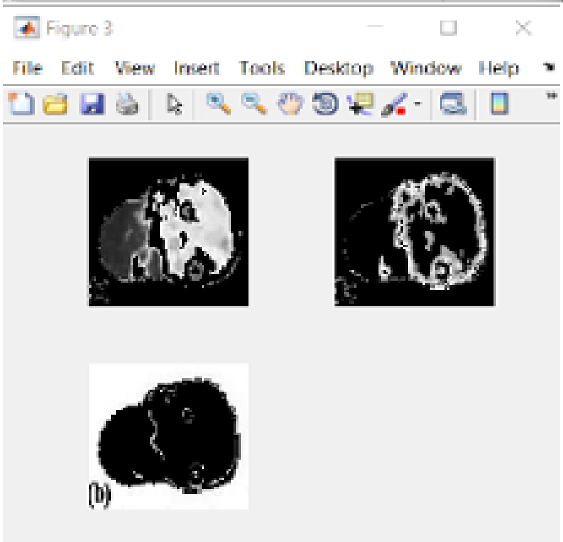
IV.RESULT AND ANALYSIS

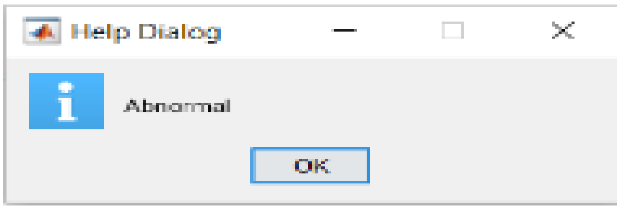
Here we have a case of a gastric cancer cell. Initial image is the original image then we have the r segmented image and we have the b-segmented followed by the result of the image. Here the cell is said to be cancerous therefore the result is abnormal in the given case.











V.CONCLUSION

The gastric cancer is the disease that cause second most number of deaths, so detection of the cancer cells in an early stage itself will reduce this rate.The conventional method used is not arithmetically precise and it is prone to errors By using the system proposed which uses deep learning algorithm, which is trained with data sets it is easy to detect the cancer cells with high accuracy and is less time consuming process.

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