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RESEARCH ARTICLE

GASTRIC CANCER DETECTION VIA DEEP LEARNING IN IMAGE PROCESSING

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Abstract – Gastric cancer (GC) is one of the leading causes of mortality from cancer around the world. It primarily affects older persons. Every year, almost six out of ten persons diagnosed with stomach cancer are above the age of 65. This paper proposed a novel GAstric cancer Detection using DEep LEarning (GADDLE) to identify the gastric cancer in an CT image. Initially the input images are pre-processed using the Gaussian adaptive bilateral filter to enhance the quality of the image. Therefore, the pre-processed images are fed into RegNet feature extraction model to for extracting the features in the image. The best features are selected by using the Dingo Optimization Algorithm. Finally, the normal and the abnormal case of the GC are classified using Link Net model. The GasHisSDB datasets are used to evaluate the performance of the proposed method of specific matrices such as Specificity, Recall, Accuracy, Precision and F1-Score. The suggested Link Net improves accuracy by 2.43%, 4.89%, and 1.98% compared to Alex Net, Google Net, and ResNet, respectively.

Keywords *– Gastric cancer, Link Net, Dingo Optimization, Reg Net.*

1. INTRODUCTION

Gastric cancer is the fifth most common cancer worldwide and the third greatest cause of cancer-related death [1]. Every year, more than a million new instances of stomach cancer are reported worldwide, making it a major public health concern. GC is still the third most prevalent cause of cancer-related death globally, despite a reduction in incidence and mortality over the last 50 years [2]. There are numerous immutable risk factors for stomach cancer, including age, sex, and race/ethnicity. Some risk factors, like smoking, eating a diet high in nitrates and nitrites, and having Helicobacter pylori infection, are under your control [3]. The survival percentage of patients with stomach cancer varies significantly based on their diagnosis date. Early detection of stomach cancer can lead to a survival rate of more than 90% [4]. GC incidence varies widely, with higher frequencies in Asia, Africa, South America, and Eastern Europe. In Western countries, the number of patients in the proximal stomach appears to be growing, despite a consistent drop in absolute incidence over recent decades [5].

In recent years, with the introduction of deep learning, artificial intelligence (AI) has increasingly been used in medical image processing and has displayed excellent performance in recognizing lesions under upper or smaller endoscopy of the stomach in different modes, such as WLE, ME-NBI, or blue laser imaging [6]. A deep learning technique identified stomach cancer with a sensitivity of nearly 100% and a specificity of 80.6% in 3212 real-world WSIs scanned by multiple scanners. In an internal test, the algorithm fared comparable to 12 pathologists in terms of assessment [7]. The Efforts are being made to improve imaging technologies and develop models for predicting the lymph nodal status of patients with early gastric cancer, but the diagnostic accuracy of endoscopic ultrasonography (EUS) and enhanced computed tomography (CT) for LNM prediction remains unsatisfactory [8]. Personalized therapy strategies for stomach cancer rely on accurate outcome prediction [9]. Therefore, novel technique has been proposed to gastric cancer in an CT image. The suggested work's main contribution is as follows.

- Initially, the input photos are pre-processed with a Gaussian adaptive bilateral filter to improve their quality.
- Therefore, the pre-processed images are fed into the Reg Net model for extracting the features in the image.
- Afterward the best features are selected from the extracted features utilizing Dingo Optimization algorithm.
- Finally, the normal and abnormal cases of the GC is classified employing Link Net model.

The rest of this study's sections are explained below: Section II reviews the research in light of existing literature. Section III provides a comprehensive description about the proposed system. The conclusion is found in Section V, whilst the results and discussion are in Section IV.

2. LITERATURE SURVEY

The detection of gastric cancer forms using deep learning techniques has been part of numerous studies in recent years. A quick summary of a few current research papers is given in the section as follows.

In 2020, Li, L., et al [10] suggested a method for analysing stomach mucosal lesions detected by M-N [BI that is based on convolutional neural networks (CNNs). The Microvascular architecture and the micro surface structure of gastric mucosal lesions are observed using Magnifying Endoscopy with Narrow Band Imaging (M-NBI), which has been used to investigate early stomach cancer. The CNN system's sensitivity, specificity, and accuracy for early diagnosis of gastric cancer were 91.18%, 90.64%, and 90.91%, respectively.

In 2020, Horiuchi, Y., et al [11] suggested a technique towards the early identification of gastric cancer (EGC), This allows the adoption of less intrusive cancer treatments. The primary goal is to investigate the extent to which the CNN system can diagnose gastritis and EGC using ME-NBI. The CNN accurately classified 220 out of 258 ME-NBI images, demonstrate the accuracy rate of 85.3%. In the future, the CNN system and endoscopists will be able to diagnose cases by confirming by biopsy whether the lesions are due to gastritis or gastric cancer.

In 2021, Wang, J. and Liu, X., [12] proposed a Deeplab v3+ neural network-based automatic model for gastric cancer segmentation. It evaluates the sensitivity, specificity, accuracy, and dice coefficient of a multi-scale input Deeplab v3+ network to SegNet and ICNet. Similar to the SegNet and Faster-RCNN models, Deeplab v3+ has an accuracy of 95.76% and a Dice coefficient of 91.66%, which is more than 12% higher. Future research should concentrate on evaluating and enhancing techniques to produce DL models for cancer diagnosis that perform better.

In 2022, Chen, H., et al [13] proposed a multi-scale visual transformer model for gastric histopathological image detection known as GasHisTransformer (GHID). The suggested approach will enable automatic worldwide detection of stomach cancer photos. With accuracy rates of 96.43% and 97.97%, GasHisTransformer and LW-GasHis-Components are tested using a dataset of stomach cancer histology. The techniques like few-shot learning and domain adaptation to address this issue in further research.

In 2021, Lee, S.A., et al [14] proposed a CADx method to diagnose and categorize cancerous diseases such gastric polyps, gastric ulcers, gastritis, and bleeding from cases of gastric cancer. In order to choose efficient treatment alternatives without requiring a surgical biopsy, this process may be quite important. In classifying cancer and non-cancer cases, this method achieved 96.3% accuracy. In the future, this study's findings will be confirmed by using the CADx system on a bigger, independent data set.

In 2022, Su, F., et al [15] suggested a deep learning (DL) system that uses hematoxylin-eosin (HE) to directly detect microsatellite instability (MSI) and interpretable tumor differentiation grade in gastric cancer. This method will gather pathological information regarding the formation of glandular structures, which is essential for differentiating between PDA and WDA. Applying the best tile fusion classifier, the integrated system achieved automatic patient-level MSI diagnosis with an accuracy of 83.87%.

In 2022, Wu, L., et al [16] proposed a system using deep learning to address numerous aspects of early gastric cancer diagnosis, including as recognizing and forecasting cancer and detecting stomach neoplasms. For a national human-machine competitors, this technique provides a cutting-edge comparison of the system to endoscopists via real-time films. The predictive system's accuracy ratings for early gastric cancer invasion depth and differentiation status were 71.43% and 78.57% respectively.

The literature review indicates that a number of techniques focus on CT input image to accurately diagnosis the gastric cancer in the early stage. Although as previously mentioned there are certain disadvantages to these approaches. To overcome this drawback a novel GAstric cancer Detection using DEep LEarning (GADDLE) have been proposed to identify GC in CT images.

3. PROPOSED METHOD

This paper proposed a novel GAstric cancer Detection using DEep LEarning (GADDLE) to identify the gastric cancer in an CT image. Initially the input images are pre-processed using the Gaussian adaptive bilateral filter to enhance the quality of the image. Therefore, the pre-processed images are fed into RegNet feature extraction model to for extracting the features in the image. The best features are selected by using the Dingo Optimization Algorithm. Finally, the normal and the abnormal case of the GC are classified using Link Net model (Figure 1).

3.1. Gaussian Adaptive Bilateral filter

The Gaussian Adaptive Bilateral (GAB) Filter is a bidirectional filtering extension that adjusts its filtering coefficients based on local image data, creating a dependable tool for image denoising with edge-preserving smoothing. This filter reduces noise in photos entered during the pre-processing step. The GAB filter effectively reduces noise from images while enhancing edge preservation and smoothness.

The technology suggested has the ability to greatly improve image quality. The bilateral filter, input image I_l, and guiding G are distinct, as illustrated in equation (1):

$$P(c) = \sum_r (w_{c,r}^{\hat{G}})(\hat{G}) I_l \tag{1}$$

Equation (1) defines I_l as the center point of the input picture, while equation (2) expresses $w_{c,r}^{G_1}$.

$$w_{c,r}^{G_1} = \frac{1}{M_c} \exp\left[-\left|\left|\frac{c-r}{-\rho_e^2}\right|\right|^2\right] \tag{2}$$

In equation (2), M_c represents the normalizing value, and the Gaussian spatial kernel is represented by exp $\left[-\left|\left|\frac{c-r}{-\rho_e^2}\right|\right|^2\right.$. The GAB kernel evaluation factor is expressed in the following equation.

$$w_{c,r}^{q,f,u}\left(I_l,\hat{G}\right) = \frac{1}{M_c}\exp\left[-\left|\left|\frac{c-r}{-\rho_e^2}\right|\right|^2\right]\exp\left[-\left|\left|\frac{I_1-\hat{G}}{-\rho_e^2}\right|\right|^2\right] \quad (3)$$

Here, $-\rho_e^2$ represents brightness fluctuations. Equations (1) and (3) provide $\hat{G}$, and the range kernel is $\exp\left[-\left|\left|\frac{I_1-\hat{G}}{-\rho_e^2}\right|\right|^2\right]$ respectively.

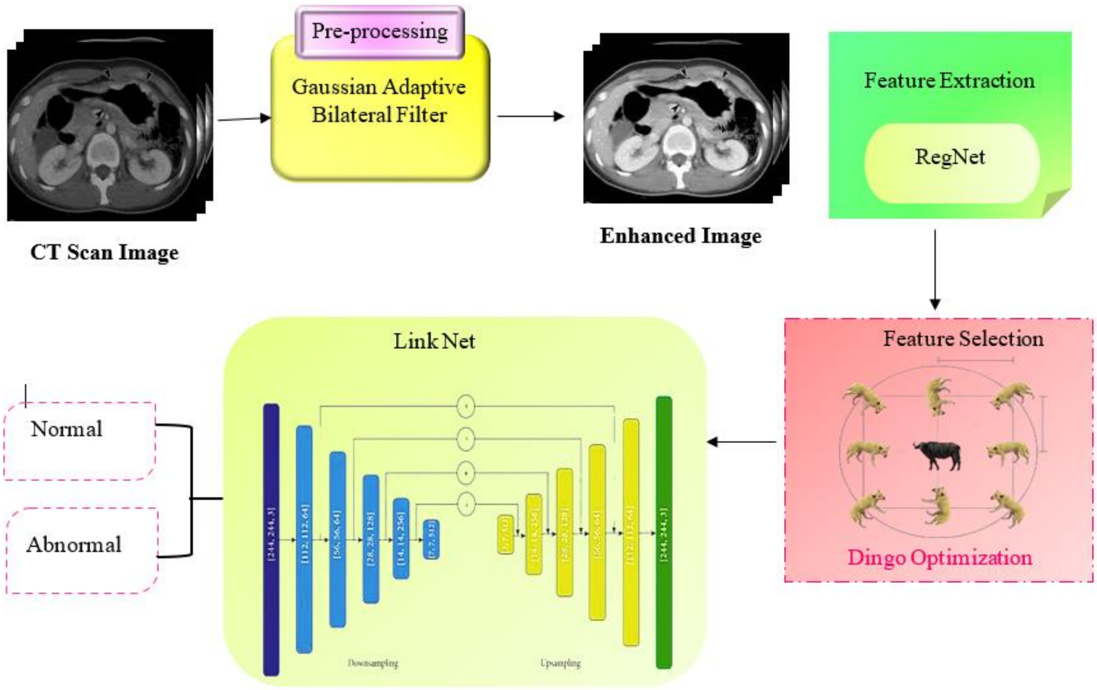

Figure 1. Work flow of proposed (GADDLE) block diagram

3.2. RegNet

Statistical features such as average, median, variation, normalized entropy, standard deviation, and kurtosis are extracted from photos using RegNet during the feature extraction process. The graphical function is based on the lightweight and efficient RegNet foundation. RegNet proceeds in four steps with ever less pixels, employing a succession of comparable units. The subsequent section A^n represents the module output, A^{n-1} represents the feature map for the nth module. The pooling method is frequently used in featured systems to reduce the overall amount of feature representations by performing the required analysis. Stride (s=1) was employed to achieve maximum pooling. The framework's maximum input size is 224x224, which is the standard dimension of data for RegNet networks.

$$P_2^n = ReLU(q_m(w_{12}^n * Y_1^n + b_{12}^n) \quad (4)$$

$$[A^n, D^n] = ReLU\left(q_m\left(conLSTM(Z_2^P[A^{n-1}, D^{n-1}])\right)\right) \quad (5)$$

The input of $ConLSTM$ inside the module is represented by the entry entity P_2^n and the previous output of $ConvLSTM\ A^n$ in equation (5). The $ConvLSTM$ determines whether the data inside the memory cell is supplied to the A^n output hidden characteristic map based on the inputs source.

3.3. Improved Dingo Optimization (IDO)

Improved Dingo Optimization's (IDO) optimization methodology is designed for feature selection, hence optimizing data and providing relevant features. Finding the most effective real-world system solutions is a difficult undertaking. Because there are plenty fantastic options accessible. Equation (1) illustrates the improvement in persecution, scavenging, collective attack, and survival.

$$\delta = (AF - MF) \quad (6)$$

$$z = \frac{mean\ (Z(F-MF))}{mean\ (X(F-AF))} \quad (7)$$

$$DA = \delta \times \left(\frac{P}{Z}\right) \quad (8)$$

In this case, the terms AF and MF represent the best and worst objective functions, respectively. Fitness is represented by F, distance by A, generality by Y and p, and arbitrarily by DA, a value ranging from 0 to 1.

3.4. Link Net

The LinkNet architecture consists of a series of encoder and decoder units that break down and reconstruct the image, respectively. Finally, the images go through a few convolutional layers. The model was created with the goal of classifying cerebral palsy. LinkNet acts as a real-time semantic segmentation network. This keeps many of the image's spatial elements. The procedure comprises connecting the encoder module's shallow feature map to the similarly sized decoder module. This method uses the shallow layer's exact position data to decrease the need for superfluous computations and parameters, which speeds up computing without sacrificing precision.

In dilated convolutions, the dilated rate f_j represents subsampling the feature map by a factor of $f_j - 1$ or adding f_j zeros between the kernel weights. Equation (15) calculates the size of the resulting f_j dilated convolution kernel for a 1*1 dilated kernel with size $a_j \times a_j$.

$$\hat{a}_j = a_j + (a_j - 1) \times (f_j - 1) = f_j \times (a_j - 1) + 1 \quad (9)$$

The LinkNet design differs greatly from neural networks in terms of pixel-wise operation. Its distinctiveness stems from the connection between the encoder and decoder. Spatial information is lost during decoding, and retrieving it from the encoder's output is difficult. LinkNet connects the encoder and decoder using non-trainable pooling indices. This link recovers spatial information lost during encoding, which is critical for the decoder's up sampling. In this architecture, the decoder has fewer parameters and shares the knowledge gathered by the encoder. This design contributes to the creation of a more efficient network for real-time cerebral palsy classification when compared to existing architectural models. Link Net Architecture shown in Figure 2.

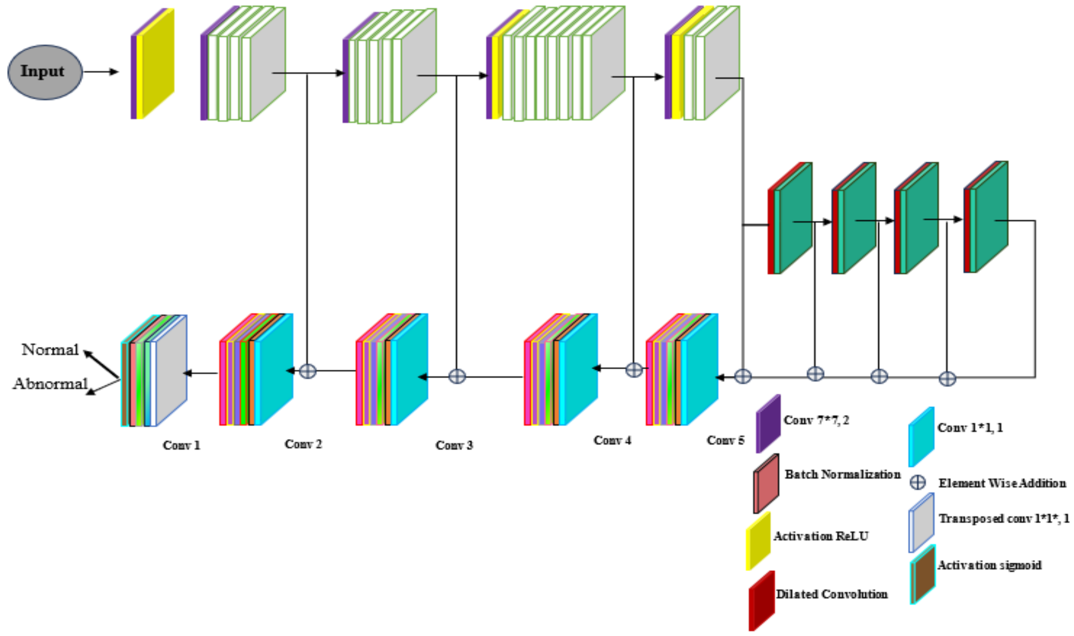

Figure 2. Link Net Architecture

4. RESULTS AND DISCUSSION

In the following section, the suggested model's efficiency is assessed using Matlab-2019b. The raw CT images are acquired from the GasHisSDB dataset [17], and they are pre-processed into appropriate frames for subsequent processing. The GasHisSDB dataset consists of 97,076 aberrant picture patches and 148,120 normal patches of images.

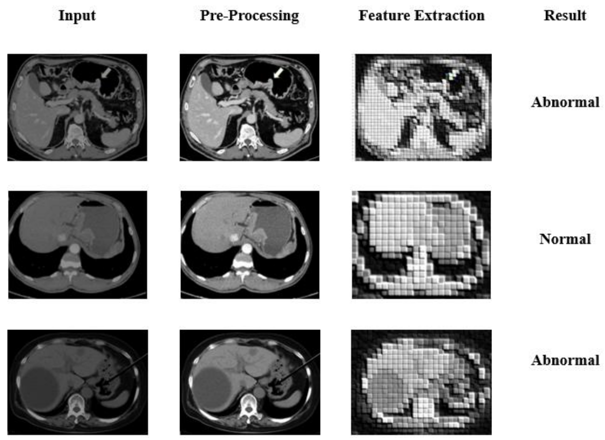

Figure 3. Experimental outcomes of the Proposed model

Figure 3 shows the visualization results of the suggested model using the acquired dataset. The input CT scans (column 1) are pre-processed with the GAB filter to remove distortions and improve the quality of the input samples (column 2). At the same time, the pre-processed OCT pictures are fed into the RegNet model to extract the features (column:3) in images. Finally, DIO algorithm is used for feature selection and the Link Net model is utilized for the classification process to detect Normal, and abnormal cases (column:4).

4.1. Performance analysis

The abilities of the proposed model were assessed using particular metrics such as specificity, accuracy, recall, precision, and F1 score.

$$S = \frac{Neg_T}{Neg_T + Pos_F} \quad (10)$$

$$P = \frac{Pos_T}{Pos_T + Pos_F} \quad (11)$$

$$Recall = \frac{Pos_T}{Pos_T + Neg_F} \quad (12)$$

$$Accuracy = \frac{Pos_T + Neg_T}{Total\ no.of\ samples} \quad (13)$$

$$F1\ score = 2\left(\frac{Pre * Re}{Pre + Re}\right) \quad (14)$$

where Pos_T and Neg_T shows the genuine positives and negatives of the CT imagery. Pos_F and Neg_F indicates false positives and negatives in CT imaging. Table.1 demonstrates the suggested model's ability to classify various stages of gastric cancer.

Table 1. Performance Evaluation of the Proposed Model

Classes	Accuracy	Precision	Recall	Specificity	F1 score
Normal	99.07	98.24	96.65	96.08	97.32
Abnormal	99.17	97.02	98.74	95.17	98.05

Table 1 shows the suggested model's usefulness in categorizing various kinds of lung cancer, such as normal and atypical instances. The suggested model achieves an accuracy of 99.12% for the LIDC-IDRI [17] dataset. Furthermore, the suggested model has overall precision, recall, specificity, and F1 scores of 97.63%, 97.69%, 95.62%, and 97.68%, respectively.

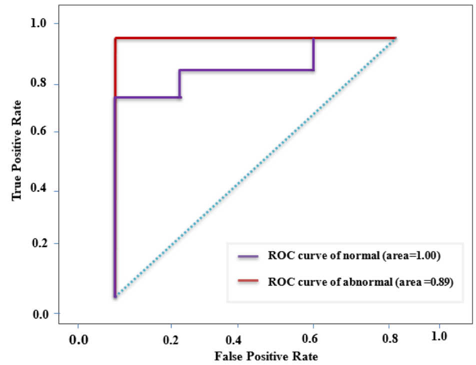

Figure 4. ROC curve of the proposed model

Figure 4 depicts the ROC computed for various lung cancer groups. The obtained CT dataset achieves a higher AUC. The suggested model produced an AUC of 0.1 for normal instances and 0.89 for abnormal cases, as assessed by the TPR and FPR parameters.

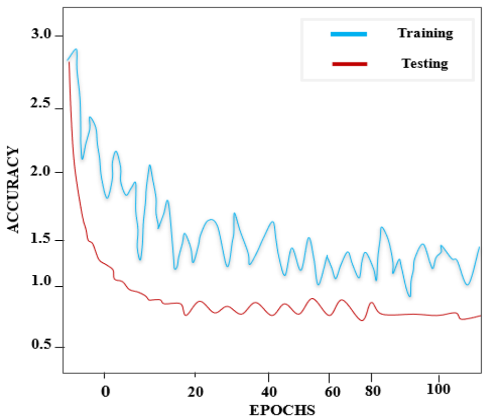

Figure 5. Accuracy curve of the proposed model

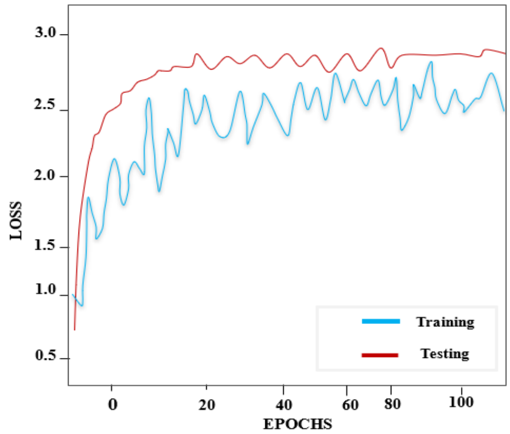

Figure 6. Loss curve of the proposed model

In Figure.5, The accuracy graph has been calculated using 100 epochs and an accuracy range. When the total amount of epochs increases, the accuracy for the suggested model improves. Figure 6 depicts the epochs and loss range, revealing that as the epochs increase, the loss of the suggested model reduces. The suggested approach achieves great accuracy in the identification of the various stages of stomach cancer using CT scans.

4.2. Comparative analysis

The effectiveness of each neural network was evaluated to ensure that the results of the proposed model are accurate. Competence evaluation was conducted between the proposed model and deep learning classifiers such as Alex Net, Google Net, and ResNet. The suggested model achieves 99.12% accuracy, which exceeds that of traditional DL networks.

According to Table 2. The suggested Link Net has a higher accuracy than classic networks such as Alex Net, Google Net, and ResNet. Link Net maintains 99.12% high accuracy ranges. Link Net achieves an accuracy rate that is more efficient than that of existing approaches. The suggested Link Net improves accuracy by 2.43%, 4.89%, and 1.98% compared to Alex Net, Google Net, and ResNet, respectively.

Table 2. Compared to conventional deep learning networks

Techniques	Accuracy	Specificity	Precision	Recall	F1 score
Alex Net	96.69	94.84	90.31	94.29	95.87
Google Net	94.23	95.59	93.51	94.67	94.43
ResNet	97.14	93.48	95.19	95.78	96.79
Proposed Link Net	99.12	95.62	97.63	97.69	97.68

According to Table 3, the proposed model enhances the overall accuracy of 2.44%, 5.04% and 4.34% better than CNN, faster R-CNN, and VGG-16 CNN respectively. According to the comparison above, the proposed model method is more reliable than existing models.

Table 3. Comparison between the suggested model and the existing models

Authors	Techniques	Accuracy
Horiuchi, et al [11]	CNN	85.3%
Wang, and Liu, [12]	DeepLab v3+	91.66%
Chen, et al [13]	GHID	97.97%
Proposed method	Link Net	99.12%

5. CONCLUSION

In this paper GADDLE technique has been proposed to identify the gastric cancer in an CT image. Initially the input images are pre-processed using the Gaussian adaptive bilateral filter to enhance the quality of the image. Then the pre-processed images are fed into RegNet feature extraction model to for extracting the features in the image. The best features are selected by using the Dingo Optimization Algorithm. Finally, the normal and the abnormal case of the GC are classified using Link Net model. The GasHisSDB datasets are used to evaluate the performance of the proposed method of specific matrices such as Specificity, Recall, Accuracy, Precision and F1-Score. The suggested Link Net improves accuracy by 2.43%, 4.89%, and 1.98% compared to Alex Net, Google Net, and ResNet. In future this research focus on AI-driven image analysis combined with physical biomarkers for more accurate stomach cancer detection.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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