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A Concise Review for Exploring Deep Learning's Potential in Gastric Cancer Prediction

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Abstract - Gastric cancer (GC) is one of the most common malignant tumours that attack the stomach lining. It is the second most common cause of cancer-related deaths worldwide. As life expectancy increased by early diagnosis and dietary patterns changes. A number of diagnostic techniques, such as endoscopy analysis, CT scans, and histopathological imaging, are frequently employed to identify and assess GC. Despite their effectiveness, these techniques are frequently labour-intensive, time-consuming, and susceptible to inter-observer variability, all of which can compromise the consistency of the diagnosis. By facilitating automated feature extraction, selection, and classification from medical images, machine learning (ML) techniques have been developed recently to aid in the detection of gastric cancer. However, ML techniques often struggle with large, complex, and high-dimensional datasets and necessitate manual pre-processing. Deep Learning (DL) has become a more sophisticated and effective way to get around these restrictions. DL models, as opposed to conventional methods and classical ML techniques, offer higher accuracy, speed, and scalability by automatically learning hierarchical features from raw medical images. An extensive review of current DL-based methods for gastric cancer detection is provided in this paper. It looks at their architectural layouts, benefits, drawbacks, and performance comparisons. In order to enhance diagnostic accuracy and clinical application of DL-based systems, the review also identifies new research trends and makes recommendations for possible future paths.

Key Words: Crime Prediction, Deep Learning, GCN-GRU, Hyperparameter tuning and Lyrebird Optimization Algorithm

1. INTRODUCTION

Criminal actions continue to be a problem as societies evolve. An increase in criminal activity has a negative effect on people's standard of living and impedes societal and economic development [1]. Improving public safety and decreasing government expenses are two outcomes of effective crime prevention. The development of better geographic information gathering tools has made it possible to accurately capture crime data across areas in this era of big data. Machine learning models have the potential to revolutionize crime prevention in many different fieldsCancer develops due to both hereditary and environmental effects. There are both genetic and environmental factors that cause cancer to grow. Environmental factors, mostly diet and social behaviour, may cause about 50% of cancer cases [1]. Tumours grow and spread over many years and in many stages. Cancer usually happens after being around harmful chemicals that cause cancer for 20 to 30 years. Modern medicine has made it possible to better identify most cancers in their later stages, when radical resection can lead to recovery in 50% of cases [2]. This paper looks at gastric cancer and other types of cancer.

1.1 Gastric cancer

Gastric cancer (GC) is a disease that can be caused by a number of things, including genetics and the environment [3]. According to current statistics, GC is the fourth most common cause of cancer deaths worldwide, and the median survival time for people with advanced stage cancer is less than 12 months [4]. Gastric carcinoma is a very aggressive cancer that is still a global health problem [5]. That's why alternative prevention, like a healthy diet, early diagnosis, and proper follow-up treatments, has led to fewer recorded incidents [6]. GC is not very common, and it is not common in people under 45 years old, where only 10% of patients have the disease.

Diagnostic Methods for Gastric Cancer: In order to identify stomach cancer or evaluate associated symptoms, traditional medical procedures including physical examinations, blood tests (such as complete blood counts and serum tumour markers like CEA and CA 19-9), barium meal X-rays, gastric lavage cytology, and exploratory laparotomies were often used [7]. Nevertheless, these diagnostic techniques are intrusive, need a high level of clinical skill, and often fall short in distinguishing between benign and malignant tumours. Additionally, their sensitivity for early-stage detection is low, which results in a delayed diagnosis and fewer alternatives for therapy.

For stomach cancer diagnosis, many imaging models are developed, including Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Endoscopy, and Histopathology [8]. The main and best method for identifying and describing stomach cancer among these models is endoscopy and histology.

1.2 Diagnosis of Gastric Cancer using Histopathology Images

Histopathology provides extremely particular information on the kind of tumour, such as adenocarcinoma or signet ring cell carcinoma, as well as the amount of differentiation and invasion of blood vessels or lymphatics. The Lauren classification, which divides GC into intestinal and diffuse subtypes, is the most often used categorisation of GC [9]. Clinical aspects, genetics, morphology, epidemiology, and expansion qualities are some of

the several traits they exhibit. Surgical choices pertaining to the variety of stomach resections are also influenced by this categorisation. Tubular and glandular components with varying degrees of differentiation are included in the intestinal subtype. Single cells with low cohesiveness and no gland development are seen in the diffuse subtype [10,11]. Furthermore, GC with signet ring cells is very common and is categorised by the Lauren classification as a "diffuse type" [12]. Signet ring cell carcinoma is now characterised as a weakly cohesive cancer form that mostly consists of tumour cells with a crescent-shaped nucleus positioned eccentrically and abundant cytoplasmic mucus [13]. GC is classified as either traditional (older than 45) or early-onset (45 years or under) based on the age upon diagnosis. Additionally, some molecules, including as HER2/neu, p53, Ki-67, and E-cadherin, may be detected by immune histochemical staining. These indicators may be used to identify individuals who may respond to certain treatments, such as trastuzumab in HER2-positive tumours, in addition to providing information on the biological behaviour of the tumour.

Figure 1 demonstrates the histopathology image of gastric cancer [14]. This histopathology image is vital for diagnosis since it clearly compares adenocarcinoma and normal stomach tissue. Histopathology allows for the precise identification of many tumor types, including those involving cellular differentiation, gland formation, invasion of blood arteries or lymphatics, and spread gastric or intestinal malignancy. The main component of diffuse-type tumors, which are easily visible, are signet ring cells. These images have the potential to impact clinical decisions by providing more precise information for the development of surgery and therapy regimens. Traditional immunohistochemistry markers, such as HER2, p53, and Ki-67, can be used to determine the efficacy of a treatment. The utilization of histopathology in stomach cancer diagnoses will guarantee intelligent, personalized, and evidence-based treatment.

1.3 Diagnosis of Gastric Cancer using Endoscopy Images

Endoscopy is a minimal invasive diagnostic method that employs a flexible tube fitted with a light and camera known as an endoscope to directly see the gastrointestinal (GI) tract's internal lining [15]. Examining the oesophagus, stomach, and duodenum is made especially easy using this technique, which enables real-time examination of mucosal surfaces and the detection of anomalies such ulcers, inflammation, polyps, or tumours. The most crucial first diagnostic procedure for suspected stomach cancer is upper gastrointestinal endoscopy, also referred to as upper endoscopy, esophagogastroduodenoscopy, or EGD. To see the stomach lining, a flexible tube with a camera is sent via the mouth into the stomach. The benefit of directly seeing the mucosa is that it gives doctors the chance to spot even the smallest alterations, such as small erosions, ulcers, or elevated lesions, which might be early indicators of gastric cancer.

Artificial intelligence (AI) models are increasingly being used to improve the prediction and detection of stomach cancer utilising imaging methods such as endoscopy and histopathology images [17]. Imaging techniques like endoscopy and histopathology are being employed more and more to enhance the prediction and diagnosis of stomach cancer via the application of artificial intelligence (AI) models [17]. Machine Learning (ML) and Deep Learning (DL), two components of AI, let doctors identify and categorise stomach lesions automatically, which improves the accuracy of diagnoses and decreases the room for human mistake. There are ML models that can help with treatment planning, identify benign from malignant stomach lesions, and forecast tumour growth [18]. Improvements in diagnostic consistency, data-driven decision-making, and fast image processing are all made possible by ML. Manual lesion annotation, which may be laborious and error-prone because of the complicated patterns and irregular forms of stomach tumours, and significant interpretation variability are still obstacles that ML must overcome.

1.4 AI in Diagnosis of Gastric Cancer

On the other hand, DL models perform better when it comes to detecting and diagnosing stomach cancer from medical photos. By dynamically learning hierarchical features from raw data, DL improves model accuracy and generalisation while overcoming a number of drawbacks of conventional ML techniques [19]. Deep Belief Networks (DBNs), Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) are notable DL models. In order to enable automatic and accurate stomach cancer diagnosis and classification, these models let doctors identify significant patterns and subtle picture characteristics from endoscopic and radiologic images [20]. Figure 3 shows how the DL model uses endoscopic pictures to identify stomach cancer.

The purpose of this research is to provide a thorough analysis of the several DL classification techniques for the diagnosis of gastric cancer. It examines the benefits and drawbacks of DL methods for identifying gastric cancer in both its early and late stages. To illustrate the relative effectiveness of different approaches and pinpoint areas in need of more investigation, a comparative analysis is provided.

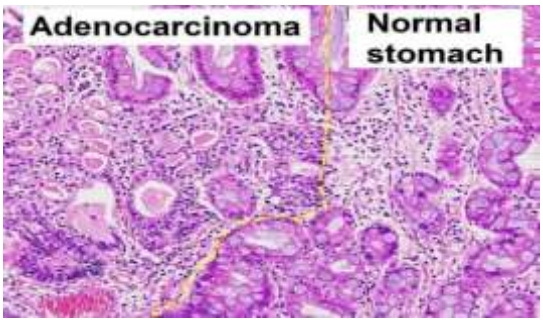

Fig -1: Sample of histopathological image of normal cells and gastric cancerous cell

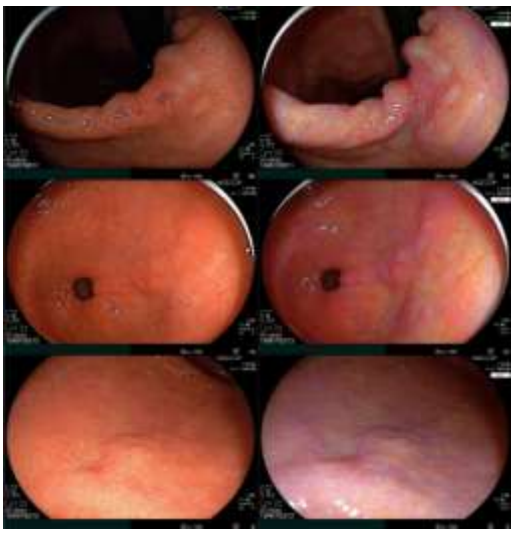

Fig -2: Endoscopy Images of Gastric cancer

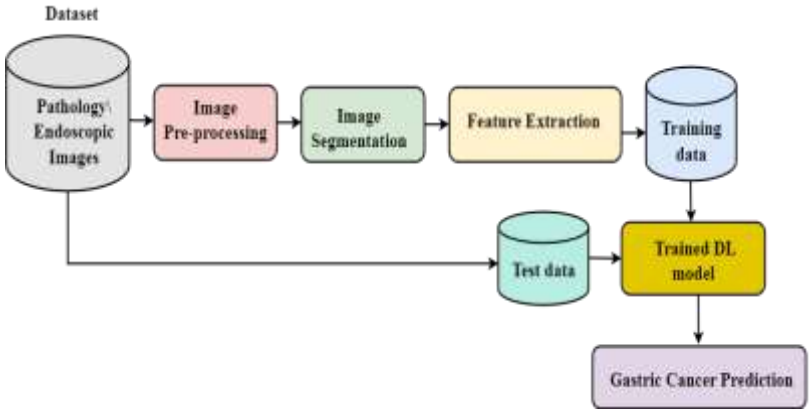

Fig -3: Gastric cancer detection by DL model using Endoscopy images

The structure of the paper is as follows: Deep learning frameworks created for the identification of stomach cancer utilising endoscopic and histopathology pictures are reviewed in Section II. The examined approaches are contrasted in Section III with respect to model design, datasets, and assessment criteria. The effectiveness of current methods is assessed in Section IV. A summary of the lessons learnt and suggestions for future research in automated stomach cancer detection are provided in Section V.

2. SURVEY ON DL BASED GASTRIC CANCER PREDICTION MODELS USING PATHOLOGY AND ENDOSCOPY IMAGES

Ahmad et al. [21] suggested an improved You Only Look Once (YOLO)-v7 model combined with a Squeeze and Excitation (SE) attention module for an automated gastric lesion identification system. The purpose of this attention-powered YOLOv7 model was to recognise tiny stomach abnormalities in endoscopic pictures, such as ulcers, adenomas, and gastric malignancies. The structure enhances feature extraction and lesion localisation by combining channel-wise attention with CNN-based object identification. By precisely identifying and categorising various kinds of stomach lesions, our model helps endoscopists during real-time endoscopic treatments.

Chae et al. [22] presented a computer-aided diagnosis (CADx) model to categorise gastroscopic pictures into healthy tissue, gastric lesions and early gastric cancer. Multi-Filter AutoAugment (MFAA), a data augmentation approach introduced in this model, filters enhanced data to preserve only relevant and high-quality samples. In the augmentation process, the Big Transfer (BiT) model acts as a supplementary filter. Healthy tissue, gastric lesions and early-stage stomach cancer were all categorised using Vision Transformer (ViT).

Jhang et al. [23] devised a Gastric section correlation network (GSCNet) for gastric precancerous lesion prediction. This model assists to diagnose corpus-predominant gastritis index (CGI) from endoscopic images of three dominant gastric sections like antrum, body and cardia. The scaling feature fusion module extracts features that robustly represent mucosa despite variations in viewing angles and scales across gastric sections. The section correlation module incorporates medical knowledge to model inter-section relationships using three correlation losses. A channel attention layer was applied to each sub-network to extract more salient deep features for early gastric cancer prediction.

Jhang et al. [23] devised a Stomach Section Correlation Network (GSCNet) to predict stomach precancerous lesions. By using the endoscopic images of the antrum, body, and cardia, this model detects corpus-predominant gastritis index (CGI). Despite the differences in viewing angles and scales amongst stomach sections, the scaling feature fusion module was employed to extract representative features accurately depict mucosa. Then, a correlation module was introduced guided by three correlation losses to capture the inter-section interactions by incorporating prior medical information. A channel attention layer was added to each sub-network to extract more salient deep information for early gastric cancer prediction

Mirza et al. [24] used Hybrid Rice Optimisation with DL (GDDC-HRODL) to create a gastrointestinal cancer detection and classification system. In order to improve visual characteristics, picture contrast was increased using Contrast Limited Adaptive Histogram Equalisation (CLAHE). For feature extraction, the HybridNet model then uses a two-path autoencoder network that collaborates with both reconstruction and classification pathways. The hyperparameters of the feature extractor were adjusted using Hybrid Rice Optimisation (HRO), and the final classification was done using an Attention-based LSTM (ALSTM). To provide precise gastrointestinal illness identification, the Ant Lion Optimisation (ALO) algorithm was used to optimise the ALSTM model.

Zubair et al. [25] presented a DL based gastric cancer prediction called DL-GHCS using digital histopathology images. Images were classified as normal or abnormal using a Gaussian Mixture Model (GMM) improved Expectation-Maximizing Naïve Bayes (EM-NB) classifier. An enhanced fuzzy c-means (IFCM) clustering technique was introduced for segmentation, which precisely identifies malignant areas. The approach highlights pertinent regions in the tissue images for early stomach cancer identification integrating Grad-CAM for interpretability for clinical diagnosis.

Tran et al. [26] created GIFCOS-DT a one-stage DL model based on the Fully Convolution One-Stage (FCOS) architecture to predict gastrointestinal tract lesions from endoscopic images. This approach improves the lesion prediction for irregular or elongated forms by using a unique Distance Transform (DT) based loss function. To speed up the processing times of every system step, a multithread approach was used. The Jetson Xavier and other edge devices use the model, which was created for real-time application, to help physicians with endoscopic treatments.

Lee et al. [27] devised an automated gastric lesion detector named theYOLO with Meta Recognition (YOLO-MR) model to efficiently detect ulcer, adenoma and cancer using endoscopic cancer. YOLOv7 was used to manage object recognition while taking into account class imbalance and the features of medical

data. To swiftly adjust to new or unbalanced data, model-agnostic meta-learning (MAML) was used. Residual blocks were used to minimize the gradient loss and facilitate deeper network learning. Gastric lesions were found by including meta-learning for optimum weights into the YOLO model.

Bui et al. [28] created a spatially-constrained and unconstrained bi-graph interaction network, known as SCUBa-Net for classifying colorectal, prostate, stomach and bladder malignancies using the multi-organ pathological images. To categorise pathology images, this model uses a bi-graph neural network (Bi-GNN) model that blends Transformers and Graph Convolutional Networks (GCNs). Each picture is processed as two graphs, one geographically unconstrained (totally linked) and one spatially limited (based on local node connections). Through specialised attention blocks, these two graph representations interact both locally and globally to effectively classify images of multi-organ cancer tissue.

Yang et al. [29] developed SegRep a mask-supervised learning technique for segment representation in pathology images for predicting stomach cancer. This method effectively extracts the specific tissue segments in pathological images. It modifies traditional CNNs by applying dual-level masking to both input images and feature maps, allowing it to focus only on target tissue regions. These masked features were then utilised to generate segment-specific, high-quality representations using a self-supervised learning (SSL) framework. Finally, stomach cancer was detected using K-Nearest Neighbour.

Almarshad et al. [30] presented a novel snake optimisation method with a DL-assisted gastrointestinal cancer classification (SOADL-GCC). This model combines a Deep Belief Network (DBN) for final classification, a Capsule Network (CapsNet) for feature extraction, and bilateral filtering (BF) for picture preprocessing. Snake Optimisation Algorithm (SOA) hyperparameter tweaking was used to maximise CapsNet's performance. The automatic categorisation of gastrointestinal cancer from endoscopic pictures is improved by this combination method.

Mudavadkar et al. [31] devised an Ensemble DL model (EDL) to diagnose stomach cancer using digital histopathology images. The decision areas of the model were visualised using Class Activation Mapping (CAM). The ensemble method makes use of VGGNet16 for fine-grained feature extraction and ResNet34 for depth-wise learning. By examining sub-size picture patches, this approach can identify stomach cancer early and may lessen the need for expensive digital scanners while increasing diagnostic effectiveness.

Almasoud et al. [32] created developed an African Vulture Optimisation Algorithm with Transfer Learning (GICDC-AVOADL) to construct a Gastro-Intestinal Cancer Detection and Classification system. An enhanced EfficientNet-B5 network is used by the model to extract deep features. EfficientNet-B5's hyperparameters were optimised using the African Vulture Optimisation Algorithm (AVOA). Furthermore, the final identification and classification of gastrointestinal malignancies was carried out using the Dilated Convolutional Autoencoder (DCAE).

Haq et al. [33] introduced an efficient hybrid cascaded DL model (HCDL) for the precise multi-classification and segmentation of stomach cancer from endoscopic images. In order to categorise endoscopic images into three categories like normal, early gastric cancer and advanced gastric cancer, the method combines a modified GoogLeNet with ViT. The Faster R-CNN technique is used in this model to precisely localise malignant areas. Following classification, Faster R-CNN creates labels and bounding boxes that precisely identify invasive regions, therefore detecting and segmenting areas of stomach cancer.

Liu et al. [34] introduced an Immune Checkpoint Inhibitors Response Network (ICIsNet) for gastric cancer. Using histopathological whole slide pictures, EfficientNet-B4, DenseNet121, and Swin Transformer V2 were trained to extract characteristics relevant to tumours. The prediction score (ICIsRS), which indicates a patient's probable response to first-line PD-1 inhibitor combination chemotherapy, was created by integrating these models into an ensemble known as ICIsNet. By determining which patients are most likely to benefit from immunotherapy, this method allows for individualised treatment planning.

Jasphin & Merry Geisa [35] developed an Multimodal DL (MMDL) model system for automated identification of gastric cancer using endoscopic images. This model makes use of three fundamental models like Xception network for classification, the Bidirectional Convolutional Gated Recurrent Unit Dense U-Net (BCGDU-Net) for segmentation, and Google's AutoAugment for data augmentation. The BCGDU-Net efficiently segments gastric lesions by combining dense convolution layers with a bidirectional Convolutional Gated Recurrent Unit (ConvGRU). For a precise prediction of stomach cancer, the Xception network then divides the segmented areas into malignant and non-cancerous groups.

Khayatian et al. [36] devised a hybrid DL (HDL) and CatBoost (CatB) method for stomach cancer diagnosis utilising histopathology images. The key areas in this model were visualised using Grad-CAM, and the feature clustering was visualised using t-distributed Stochastic Neighbour Embedding (t-SNE). Softmax was used for the prediction of stomach cancer, while EfficientNetV2B0 was used for feature extraction.

Park et al. [37] created a lightweight hyperspectral imaging system combined with artificial intelligence for gastric cancer detection. In order to capture intrinsic tissue optical features, our model made use of hyperspectral imaging and structured lighting. Based on these characteristics, a ViT model is used to categorise tissue types such as normal, adenoma, and malignancy. Accurate stomach cancer identification was made possible by the development of a revolutionary image processing technique that aligns pathology data with imaging at the pixel level.

Zhang et al. [38] constructed a Multimodal Severity rating of stomach Cancer (MSGC), a multimodal approach for rating the severity of stomach cancer utilising endoscopic images and diagnostic texts. This model adopts Bidirectional Encoder Representations from Transformers (BERT) for semantic text interpretation and an improved Residual Network with Aggregated Transformations (ResNeXt) for visual feature extraction. Through the alignment of same-category samples in the feature space, contrastive learning enhances intra-class similarity. A multi-head attention module (MHAM) highlights key characteristics. To encourage reciprocal learning across visual and textual modalities, a unique loss function combines contrastive loss with cross-entropy loss.

Kang et al. [39] developed a DL-based clinical decision support system (DL-CDSS) for early gastric cancer prediction. This model predicts lymph node metastases and lymphovascular invasion in patients for cancer prediction by combining

endoscopic pictures with real-world clinical data, such as demographics, biopsy results, and CT findings. The transformer model combines a multimodal classification model that combines CNN and random forest (RF) with an image-only model that uses a simple CNN. Whether a patient should have a gastrectomy or endoscopic resection, this method helps doctors make well-informed judgements.

Zubair et al. [40] created a multi-channel attention mechanism (MCAM) in conjunction with transfer learning (TL) to categorise stomach cancer using histopathology images. With CNN backbones (Inception-V3, VGG-16, and Xception, respectively), this model combines three complementing attention channels, such as multi-scale global information, multi-scale spatial information, and multi-scale spatial information. Together, these channels improve model interpretability and feature extraction, especially when using Grad-CAM visualisations. The framework is intended for the categorisation of medical images, particularly to help with the early and precise detection of stomach cancer from histopathology slides.

Khan et al. [41] constructed a network-level fused DL technique to classify gastrointestinal cancer using wireless capsule endoscopy (WCE) images. Sparse Convolutional DenseNet201 with Self-Attention (SC-DSAN) improves feature concentration on illness areas and lowers computing burden by using sparse convolutions and self-attention. CNN-GRU captures temporal relationships in WCE picture sequences by combining CNN for spatial feature extraction with a Gated Residual Unit (GRU). The Entropy-controlled Marine Predators Algorithm (EMPA) and Bayesian Optimisation (BO) were used to optimise the features. Lastly, a Shallow Wide Neural Network (SWNN) was used to classify gastrointestinal cancer.

The comparison of several DL-based gastric cancer prediction models utilising pathological and endoscopic images is shown in Table 1.

Table -1: Assessment of Various DL Based Gastric Cancer Prediction using pathology and endoscopy images

Ref No, Author & year	Techniques Used	Advantage	Disdvantage	Dataset	Performance Evaluation
[21] Ahmad et al. (2023)	YOLOv7 object detection model, CNN with SE attention module	Effective small lesion localization, reduces dependence on endoscopist expertise,	Needs large annotated dataset, Model trained on private data, may not generalize well	61,734 endoscopic images collected from a hospital in Korea (2018–2021)	Precision: 72%; Recall: 69%; F1-Score: 71% mean Average Precision (mAP): 71%
[22] Chae(2023)	ViT, MFAA, BiT	Better generalization due to filtering low-quality augmented data, Works well on complex medical images	High computational cost, loner training time, lower accuracy on larger datasets	Gyeongsang National University Hospital and AI Hub, Korea with endoscopic images of 600 healthy tissue images, 300 abnormal lesion images, 300 early gastric cancer images	Abnormalities vs Healthy Tissue F1-score: 0.87 Area Under Curve (AUC): 0.94 EarlyGastric Cancer vs. Non-Cancerous Lesions F1-score: 0.92 AUC: 0.97
[23] Jhang (2023)	Scaling Feature Fusion Module, Section Correlation Module, Channel Attention Layer	Applies prior medical knowledge, effectively handles variation in image angles and scales	Complex design may not suit low-resource settings, Image quality variations can reduce performance	304 patients, each patient has 3 endoscopic images collected from two hospitals in Taiwan	Accuracy = 95.7%; Sensitivity: 93.8%; Specificity: 96.2%
[24] Mirza (2023)	HybridNet, HRO, ALSTM, ALO, two-path autoencoder network	Enhances image clarity, better hyperparameter optimization, Handles both labeled and unlabeled data	Multiple optimization steps leads to increases training time, Repeated retraining due to different datasets	Kvasir Dataset with 5,000 labeled endoscopic images	Accuracy = 99.49%; Sensitivity = 98.72%; Specificity = 99.68%; F1-score: 98.72%

[25] Zubair (2024)	NB classifier with GMM, EM algorithm IFCM, Grad-CAM	Lower computational complexity, visual explanations,	Longer training time, depends upon manual feature extraction	GasHisSDB: 245,196 histopathology images HCRF: 700 H&E-stained images with ground truth segmentation	Accuracy (GasHisSDB) = 98.47% Accuracy (HCRF) = 97.31%
[26] Tran (2024)	Multithread technique, FCOS, DT	Better detection of irregular-shaped lesions, real –time capability	Lower accuracy on subtle lesions, performance drops with low-resolution input	Kvasir-SEG with Public dataset with 1,000 polyp images. IGH_GIEndoLesion-SEG with 5,211 endoscopic images from 2,543 patients	Average Precision (AP) 50 (Kvasir-SEG): 81.3% (GIFCOS-DT), +4.2% over FCOS AP50 (IGH_GIEndoLesion-SEG): 57.5% (GIFCOS-DT), +7.2% over FCOS
[27] Lee (2024)	YOLOv7, MAML, Residual Blocks	Handles class imbalance effectively, achieves high accuracy even with limited data	Longer training time due to meta-learning, computationally expensive during training phase.	Dataset Gachon University Gil Medical Center, including 61,734 endoscopic images across cancer, ulcer, adenoma, normal.	Accuracy = 96%; AP (Cancer) = 0.984 AP (Ulcer) = 0.919 AP (Adenoma) = 0.976
[28] Bui (2024)	Bi-GNN. GCN, transformers, specialized attention blocks	Captures both local and global tissue relationships, effective multiple cancer types and organs	High computational complexity and training cost, Limited external validation on some cancer types	Pathology image dataset of Colorectal cancer,Prostate cancer,Gastric cancer,Bladder cancer	Accuracy Colorectal cancer: 89.0%; Prostate cancer: In-domain test: 72.1% Out-of-domain test: 74.9% Gastric cancer: 85.9%; Bladder cancer: 93.0%
[29] Yang (2024)	SSL, dual level masking, KNN	Captures object-specific tissue features; Avoids overfitting issues	Depends on high-quality segmentation masks; limited evaluation on multi-institutional data	Gastric cancer (GC) dataset (pathology images) from University of Tokyo (171 WSIs, 140 patients)	Accuracy: Foveolar: 90.7% Gland: 86.7% Differentiated cancer: 94.4% Undifferentiated cancer: 89.8% Cluster Homogeneity (AUC): 0.801
[30] Almarshad (2024)	BF, CapsNet, SOA, DBN	Enhances edge preservation in images, Maintains spatial relationships, fine-tuned hyperparameters	Scalability issues, high model complexity due to integration of multiple components	Kvasir dataset with 5000 labeled endoscopic images.	Accuracy = 99.72%; f1-SCORE = 99.29%
[31] Mudavadkar (2024)		Detects cancer from small image patches, effective feature extraction task	Longer training, low sensitivity, Longer training, low sensitivity,	GasHisSDB (Gastric Histopathology Sub-Size Image Database with 245,196 image patches from 600 high-resolution pathology slides.	Accuracy (80*80 patch size) = 99.3%, Accuracy (120*120) = 99.4%, Accuracy (160*160) = 98.4%

[32] Almasoud (2024)	Improved EfficientNet-B5, AVOA, DCAE	capture detailed features without losing image information, less computation time	Finds harder to interpret for clinical validation, trained on low-resolution images	Kvasir dataset with 5000 labeled endoscopic images across 5 GI classes	Accuracy: 99.64%; Precision: 99.09%; Recall (Sensitivity): 99.11%; F1-score: 99.09%
[33] Haq (2024)	GoogLeNet, ViT, Faster R-CNN	Effectively captures spatial-global feature and robust generalizability, Efficient segmentation task	Low-frequency tumors excluded; same-source images reduce diversity; few positives limit sensitivity	Total of 1,741 endoscopic images, collected from a Guangdong hospital, with 67 healthy, 891 early-stage and 783 advanced gastric cancer cases.	Accuracy = 97.4%; Sensitivity = 97.5%; F1-score = 95.9%
[34] Liu (2024)	EfficientNet-B4, DenseNet121, Swin Transformer V2,	Predicts immunotherapy response directly from biopsy slides, No extra testing needed, efficient extraction of complex patterns	lacks transparency, relatively small sample size and class imbalance, Manual ROI Labeling	313 H&E-stained whole slide Pathology images from 264 patients with advanced gastric cancer collected from 4 medical centers in China like FAH-SYSU, FAH-NCU, SAHSYSU, ACH-GZMU	Accuracy (FAH-SYSU) = 84.8%, Accuracy (FAH-NCU cohort) = 87.0%, Accuracy (SAH-SYSU cohort) = 93.2%, Accuracy (ACH-GZMU cohort) = 90.0%.
[35] Jasphin (2024)	Google's AutoAugment BCGDU-Net - Xception	AutoAugment reduces overfitting and improves generalization, better lesion segmentation using bidirectional memory	Increases training time due to large data volume, might may overfit if segmentation was inaccurate	480 endoscopic images, 230 for training (53 cancerous, 180 non-cancerous) 240 for testing (30 cancerous, 190 non-cancerous)	Accuracy: 98.9%; F1-Score: 98.89%
[36] Khayatian (2024)	EfficientNetV2B0), CatBoost classifier, Grad-CAM, t-SNE	Efficient visualization and handles large feature set	Manual Feature Selection, limited data diversity	GasHisSDB Contains Gastric histopathology images with 80, 120 and 160 pixel crops	Accuracy 80px = 89.7%, 93.1%, and 120px = 93.9% 160px = 93.9%
[37] Park (2025)	hyperspectral imaging system, ViT	Effectively handles high-dimensional and heterogeneous data, Better pixel-wise analysis	Limited sample size, lacks depth data, image synchronization issues	9 patients' gastric tissue specimens (6 cancer, 3 adenoma) Histopathology images collected via ESD at Ajou University Hospital (2022–2023)	Accuracy = 0.913; Precision= 0.891; Recall = 0.854 F1 Score = 0.867; Specificity= 0.930
[38] Zhang (2025)	ResNeXt, BERT, Contrastive learning, MHAM	Captures complementary visual-textual features, performs well on both small and large database	Dependence on multi-modal data availability, imbalance or noise hinders feature alignment	private dataset collected from a local hospital, comprising endoscopic images and diagnostic records.	Accuracy = 94.14%, Precision = 94.84%, Recall = 93.69%, F1-score = 94.26%.

[39] Kang (2025)	Transformer-based multimodal DL model, Basic CNN model (image-only) CNN + RF (multimodal fusion)	Captures complex patterns across data types, image and clinical data for better decision-	Utilized only single mode patient data might not generalize, more text data was used than images	2927 patients with early gastric cancer from 7 institutions Endoscopic images + clinical data (demographics, biopsy, CT) Internal Validation: 449 patients External Validation: 766 patients (from 2 hospitals)	Accuracy: 91.3%; Sensitivity: 89.8%; Specificity: 91.5%;
[40] Zubair (2025)	MCAM, TL, Inception-V3, VGG-16, Xception, Grad-CAM	Extracts both global and local features from images, captures relevant image regions	Drop in performance on low-resolution images, limited interpretability and scalability	GasHisSDB: Gastric histopathology images (three sub-datasets A: 160x160, B: 120x120, C: 80x80) and HCRF, histopathology dataset	Accuracy (GasHisSDB) = 99.6% Accuracy (HCRF) = 99.65%
[41] Khan (2025)	SC-DSAN, CNN, GRU, BO, EMPA, SWNN	Lowers processing load and memory use, capture more relevant disease features, well optimized parameters	High Training Time, Slight complexity in GRU while training on larger datasets	Kvasir-V1, V2 endoscopic images with 8 gastrointestinal cancer disease classes, 4000 images per class after augmentation	Accuracy (Kvasir-V1) = 99.60%, Accuracy (Kvasir-V2) = 96.60%

The assessment Table 1 shown that the methods using various DL algorithms for both endoscopic and histopathology images are suffered from class imbalance issue. It was solved by many augmentation approaches, transfer learning approaches and meta-learning approaches. However, obtaining the unique characteristics of the images for handling class imbalances is very challenging. In order to solve these issues, an intelligent augmentation method can be developed for generating images by learning unique characteristics of images from small datasets.

3. RESULT AND DISCUSSION

The performance analysis of the deep learning methods presented in Table 1 highlights their effectiveness in predicting and classifying gastric cancer using both pathology and endoscopic images. Most of the studies utilized different benchmark or institution-specific datasets, reflecting a wide

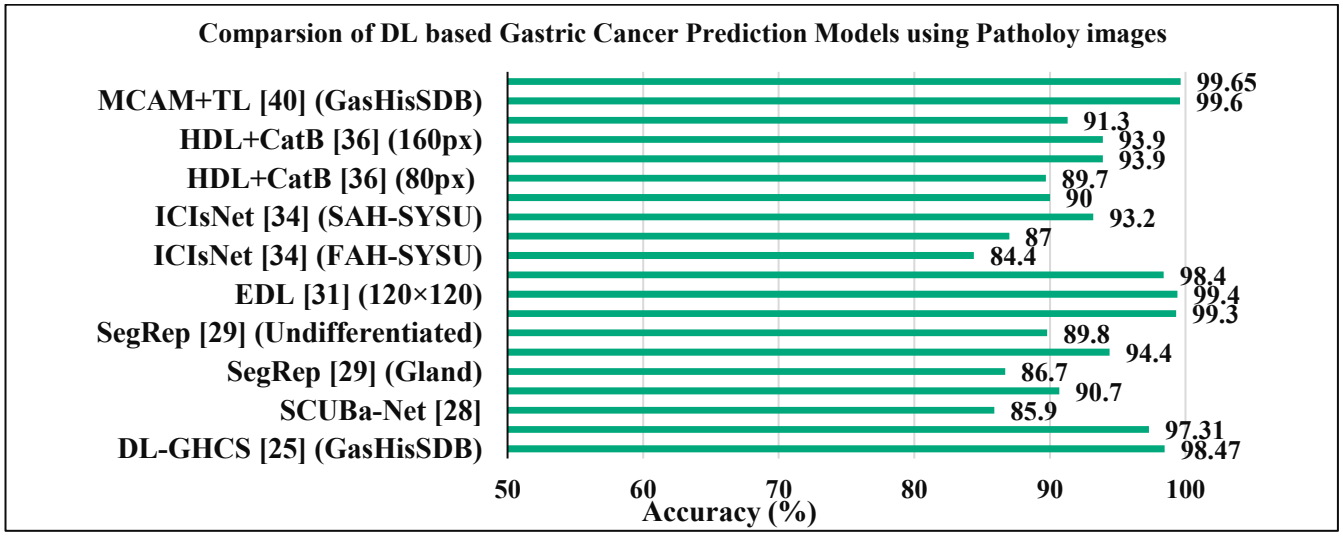

Fig -4: Graphical analysis of various DL based gastric cancer prediction models using pathology images in terms Accuracy

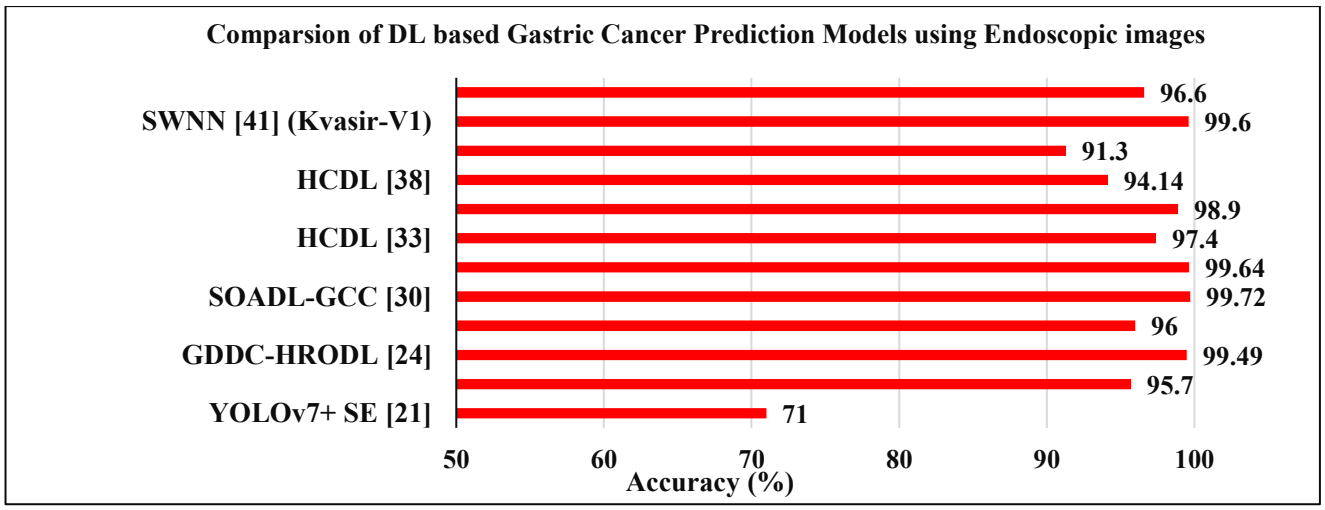

Fig -5: Graphical analysis of various DL based gastric cancer prediction models using endoscopic images in terms Accuracy

range of imaging sources and clinical settings. In this section, a comparative performance evaluation is conducted across deep learning-based gastric cancer prediction models focusing primarily on classification accuracy.

Figure 4 depicts the graphical representation of different DL based gastric cancer prediction models using pathology images by accuracy metrics. Among the compared prediction models, MCAM+TL [40] for HCRF based histopathology image dataset results in highest accuracy of 99.65% compared to other models. This model effectively extracts both global and local features from images and captures relevant image regions for gastric cancer prediction.

Figure 5 depicts the graphical representation of different DL based gastric cancer prediction models using endoscopic images by accuracy metric. Among the compared models, SOADL-GCC [30] results in highest accuracy of 99.72% when evaluated on Kvasir dataset with 5000 labeled endoscopic images.This model effectively preserves image edges, maintains spatial relationships, and utilizes fine-tuned hyperparameters to enable efficient and accurate gastric cancer prediction.

Based on Figures 4 and 5, it can be concluded that the MCAM+TL [40] model, evaluated on the HCRF histopathology image dataset, outperforms other gastric cancer prediction models that utilize pathology images. Despite its advantage, certain limitations like reduced performance on low-resolution images, along with limited interpretability and scalability on larger database which significantly lowers the models performances. Likewise, SOADL-GCC [30], evaluated on the Kvasir endoscopic dataset, outperforms other gastric cancer prediction models based on endoscopic images But, this model leads to scalability issues and increased model complexity due to the integration of multiple components. Thus, the limitations of these models will be resolved in the future proposed models by introducing the advanced and lightweight architectures aimed at improving scalability, reducing computational complexity and enhancing interpretability. Additionally, integrating both pathological and endoscopic images in a multi-modal framework enhances prediction performance and generalizability by combining cellular- and tissue-level features leading to improved diagnostic accuracy, lesion localization and clinical decision-making. These improvements will assists to develop more reliable and accurate clinical diagnostic prediction algorithms, which may someday be used for other purposes including identifying thyroid nodules in ultrasound pictures.

4. CONCLUSION

Early gastric cancer prediction reduces the morality rate. Traditional models fail to provide accurate results in the early detection. To overcome challenges, numerous deep learning (DL) models have been developed. This paper presents a comprehensive review of DL-based gastric cancer prediction approaches utilizing endoscopic and pathological images, analyzing the techniques employed, their advantages and limitations, datasets used, and performance metrics. This study provides valuable insights for researchers aiming to develop robust and efficient diagnostic models, ultimately contributingto personalized treatment strategies for patients. Future work will focus on designing advanced and lightweight architectures that improve scalability and computational efficiency, thereby enabling real-time prediction. Moreover, the integration of both pathological and endoscopic images will to enhance diagnostic accuracy, improve lesion localization and support more informed clinical decision-making for gastric cancer prediction.

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