Optimizing Gastric Cancer Classification with QCNN and Fine-Tuning

Original Scientific Paper

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Abstract *– Cancer ranks as one of the primary contributors to morbidity and mortality worldwide, standing as the second leading cause of death on a global scale. According to data from the National Cancer Registry Program of the Indian Council of Medical Research, over 1300 individuals in India lose their lives daily as a result of cancer-related causes. Gastric cancer is among the top five most prevalent cancers globally, after cancer in the lung, breast, colorectum, and prostate, highlighting the importance of accurate classification for effective treatment strategies. In this study, a novel approach utilizing a Quadratic Convolutional Neural Network combined with Extreme Learning and Fine-Tuning technique, a deep learning architecture specifically designed to capture intricate patterns and features within medical imaging data. Fine tuning technique is used to enhance the model's generalization capability and adaptability to diverse datasets. Through extensive experimentation and validation on a comprehensive dataset comprising gastric cancer images, the proposed approach achieves an impressive accuracy of 94%. The findings indicate the efficacy of the proposed approach for classifying gastric cancer. With its high accuracy and robust performance, the developed QCNN model holds promise for assisting clinicians in accurate diagnosis and prognosis of gastric cancer patients, ultimately contributing to improved patient outcomes and personalized treatment strategies.*

Keywords: *Deep learning, Digestive system, Quadratic Convolutional Neural Network, Endoscopy, Gastric cancer, Extreme Learning, Fine tuning*

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1. INTRODUCTION

Gastric cancer, also referred to as stomach cancer, is a malignant tumor that develops in the stomach [1]. Various factors contribute to its development, including Helicobacter pylori infection, dietary habits, smoking, genetic predispositions, and familial history [2]. The structure and function of the stomach provide important context for understanding gastric cancer and its impact on the body. The stomach is a vital organ in the digestive system, connecting the esophagus to the small intestine [3]. Structurally, it is J-shaped with distinct regions: the cardia, fundus, body, and pylorus. Lymph nodes surround it, aiding in immune response. The pylorus serves as a connection to the duodenum, with the pyloric sphincter facilitating stomach emptying [4]. The greater curvature forms a convex lateral surface, while the lesser curvature creates a concave medial border. This complex anatomy supports the stomach's role in digestion and underscores its importance in overall health. Understanding the intricate anatomy of the stomach is crucial in recognizing the early symptoms and improving the prognosis of gastric cancer through timely detection and intervention.

Early symptoms may be nonspecific, making early detection challenging. Gastric cancer prognosis heavily relies on the stage of diagnosis, highlighting the critical importance of timely detection for effective treatment and improved outcomes [5]. Timely identification of gastric cancer is crucial for improving patients' survival rates. The disease often progresses asymptomatically or with mild symptoms in its initial stages, leading to delayed diagnosis and treatment initiation. As gastric cancer advances, it becomes more difficult to treat, with limited therapeutic options and poorer outcomes [6]. Therefore, early detection through screening programs enables the identification of tumors at an earlier, more treatable stage, facilitating curative interventions such as surgery, chemotherapy, or radiation therapy. Improved prognosis associated with early detection underscores the significance of developing accurate and efficient diagnostic methods for gastric cancer.

Convolutional neural network (CNN) have transformed medical image analysis by allowing automated interpretation of diagnostic images with exceptional accuracy and efficiency [7]. CNN excel at learning hierarchical representations of image features directly from raw data, eliminating the need for handcrafted features or domain-specific knowledge. Through the use of large annotated datasets, CNNs can identify subtle patterns and abnormalities in medical images, aiding in disease detection, classification, and prognosis. In the context of gastric cancer detection, CNNs offer a promising approach for analyzing endoscopic images, histopathological slides, and radiological scans to assist clinicians in identifying suspicious lesions. Gastric cancer classification has been extensively studied due to its critical role in improving patient outcomes. Various deep learning approaches, such as CNNs, ResNet, and EfficientNet, have demonstrated significant potential in analyzing endoscopic and histopathological images. However, these methods often face limitations such as overfitting on small datasets, difficulties in capturing intricate patterns unique to gastric cancer, and reduced generalizability across diverse patient populations. These challenges highlight the need for more advanced and adaptable models capable of addressing these limitations while maintaining high accuracy in classification.

The main goal of this research is to create and assess a new method for detecting gastric cancer, which integrates a Quadratic Convolutional Neural Network (QCNN) with Extreme Learning and Fine Tuning techniques [8-9]. By doing so, we aim to improve the sensitivity, specificity, and overall accuracy of gastric cancer detection while also addressing the shortcomings of current diagnostic methods. Specifically, the study seeks to:

1. Investigate the feasibility and effectiveness of QCNN in analyzing gastric cancer-related imaging data.
2. Explore the integration of Extreme learning and Fine tuning techniques to optimize model performance and generalization.
3. The performance of the method was thoroughly evaluated on a diverse dataset comprising gastric cancer images.
4. Compare the diagnostic accuracy of the QCNN approach with current deep learning models for gastric cancer detection.

2. LITERATURE REVIEW

In their study, Lee et al. [10] developed a multilayer feedforward neural network using a scaled conjugate gradient backpropagation technique. The World Health Organization (WHO) recognizes cancer as a heterogeneous disease with various subtypes, highlighting the critical importance of early prognosis and diagnosis to improve survival rates. Therefore, there is an increasing need in cancer research to facilitate subsequent clinical management of patients. The authors identified 10 amino acid biomarkers in saliva and extracted 19 fingerprint Raman bands generated by these biomarkers, which can effectively differentiate between cancer patients and healthy individuals. Back propagation was employed to minimize the network error, while scaled conjugate gradient backpropagation was utilized for training the artificial network classifier. The approach yielded an accuracy of 92.27.

Qiu et al. [11] aimed to enhance the efficiency of GC diagnosis by utilizing DL algorithms to aid in diagnosing gastric cancer. Lesion samples in the images were annotated by multiple endoscopists with extensive clinical experience. The acquired training set was input into a CNN for training, resulting in the algorithm model DLU-Net identified with an overall accuracy of 94.1%. A cascaded deep learning model was suggested by Teramoto et al. [12] to identify the invasive location and categorize endoscopic images. Two different U-Net models are used to segment the images labeled as cancer based on the amount of invasion by stomach cancer.

Deep CNN was utilized by Xie et al. [13] to achieve automatic categorization of pathological images related to stomach cancer since DCNN is capable of efficiently extracting deep characteristics from images. A CNN architecture was developed by Hatami et al. [14] for the identification of stomach cancer. The authors were motivated by the concept of the fire module to decrease the architecture's size and improve the model's classification accuracy. The findings indicate that this model has an 89% classification accuracy.

A model based on the Deeplab v3+ neural network was proposed by Wang et al. (2021) [15] to increase the effectiveness of gastric cancer. With a 92.76% accuracy rate and a 91.66% Dice coefficient, the model outperforms the SegNet and Faster-RCNN models by over 12%. Additionally, the model's parameter scale is significantly lowered. An approach called U-Net R-CNN was proposed by Teramoto et al. in (2021) [16] based on a semantic segmentation method. In order to identify stomach cancer, U-Net was presented as a semantic segmentation technique. The primary constraint of the strategy is the limited quantity of images used for training.

A strategy for identifying and classifying gastric cancer areas from gastrointestinal endoscopic images was developed by Shibata et al. in 2020 [17] using Mask R-CNN. The results suggest that the sensitivity per image was 96.0%.

The CNN-based approach was introduced by Li et al. [18] to assess stomach mucosal lesions detected by M-NBI. CNN's diagnostic accuracy for early-stage stomach cancer was 90.91%. GoogLeNet, a deep neural network architecture, was employed by Horiuchi et al. (2020) [19] to identify stomach cancer. With 220 of the 258 images properly diagnosed, the accuracy was 85.3%. The nature of this investigation is retrospective. Table 1 provides an overview of recent research on the identification of stomach cancer, highlighting a range of strategies and techniques.

Table 1: Summary of recent works on gastric cancer detection

Author, Reference & Year	Methodology	Remarks
Lee et al. [10] 2021	Multilayer feedforward neural network back propagation technique	Achieved 92.27% accuracy in cancer detection based on saliva biomarkers and Raman spectroscopy. Performance may vary based on the number of neurons and hidden layers in the neural network.
Qiu et al. [11] 2022	CNN	Achieved 94.1% accuracy in identifying different types of lesions. Limited to the analysis of gastro scopic images.
Teramoto et al [12] 2022	Cascaded deep learning model and U-Net models.	Limited to endoscopic images collected from a single facility.
Xie et al. [13] 2023	DCNN with Adapted GoogLeNet and AlexNet models for gastric cancer diagnosis.	Improved sensitivity using GoogLeNet and AlexNet models. Also significantly reduces the computational burden.
Hatami et al. [14] 2020	CNN incorporated with fire module architecture for increased accuracy.	Achieved 89% classification accuracy on a dataset of gastric disease images. Limited to classification of gastric diseases observed through endoscopy.
Teramoto et al. [16] 2021	Developed a U-Net R-CNN model for object detection in gastric cancer images, combining semantic segmentation.	Limited by a small number of images collected from a single facility, affecting generalizability.
Shibata et al. [17] 2020	Utilized Mask R-CNN for detection and segmentation of early gastric cancer regions from endoscopic images.	The suggested approach was implemented utilizing the information gathered from a solitary establishment.
Li et al. [18] 2020	CNN-based system using narrow-band imaging (M-NBI).	Achieving 90.91% accuracy in diagnosing early gastric cancer. Limited the study to non-polypoid and non excavated lesions, restricting the applicability of the CNN system.
Horiuchi et al. [19] 2020	Employed GoogLeNet for diagnosing MENBI images of lesions undergoing endoscopic sub mucosal dissection (ESD) treatment.	Achieved an accuracy of 85.3% in identifying lesions. Retrospective study design with limited clarity in some images, potentially impacting diagnostic accuracy.

3. METHODOLOGY

A novel approach is introduced for identifying and classifying gastric cancer through the application of deep learning techniques from stomach endoscopy images. Three main steps make up the methodology: feature extraction, classification, and preprocessing. A visual illustration of the suggested methodology is shown in Fig. 1. For classification, the QNN is utilized as the primary classifier, leveraging its ability to effectively classify complex patterns in medical images.

Additionally, extreme learning and fine-tuning techniques are applied to further enhance the performance of the classifier, refining its ability to accurately detect and categorize gastric cancer.

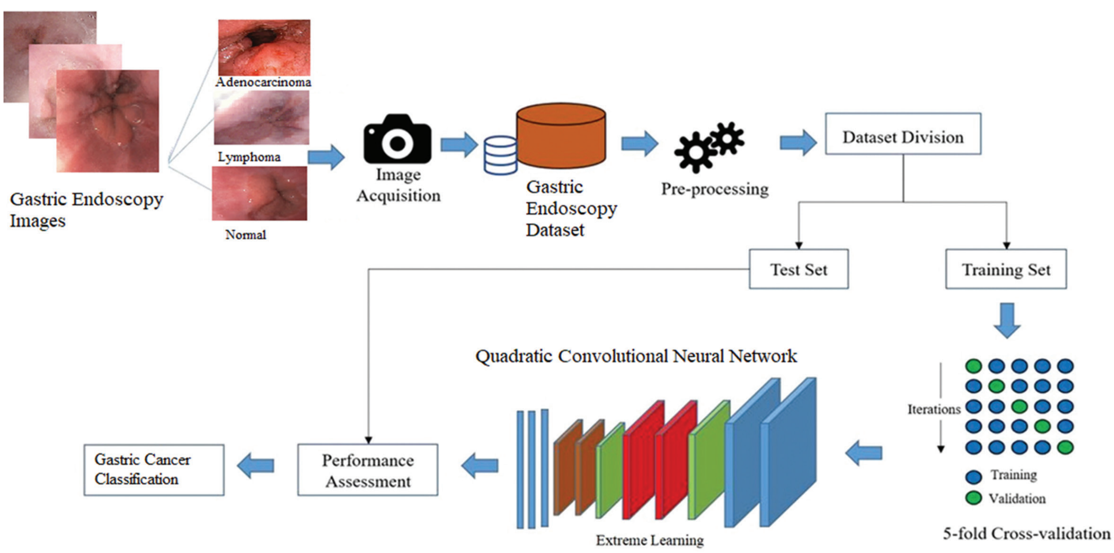

Fig. 1. Flow diagram of the proposed work

3.1. DATASET

The dataset provides a useful tool for the suggested deep learning model for the detection and categorization of stomach cancer. The endoscopic images from the Fujita Health University Hospital database comprised the dataset used in this investigation. These images are standardized to a size of 256×256 pixels and are represented in the RGB color space. The dataset includes images representing two types of gastric cancer and healthy control images. Each category within the dataset presents a diverse range of endoscopic views and pathological conditions, providing a comprehensive representation of gastric abnormalities for analysis and classification. With images standardized in size and color space, and categorized into relevant groups, the dataset facilitates consistent and reliable analysis, enabling researchers to effectively assess the performance and generalizability of the developed classification system across different pathological conditions and patient populations. Fig. 2 presents sample images from the gastric cancer dataset, providing visual examples of the types of endoscopy images used in the study for classification purposes.

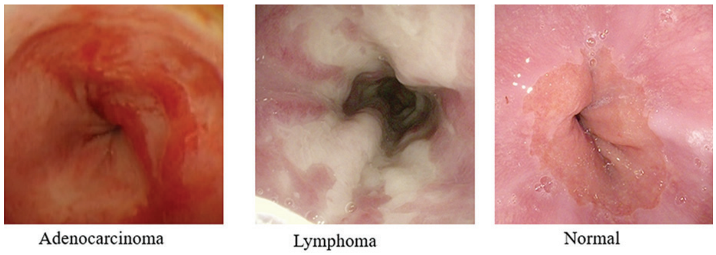

Fig. 2. Sample images from the dataset

3.2. DATA PREPROCESSING AND AUGMENTATION

In the data preprocessing and augmentation phase, two key techniques are applied to the images obtained from the gastric endoscopy dataset, which are image augmentation and image resizing. Image augmentation is a critical step aimed at enriching the diversity and quantity of images in the dataset, which is essential for effectively training deep neural networks. This technique involves applying various image processing operations such as flipping, rotation, and cropping to generate a new augmented version of the original image. Flipping involves mirroring the image horizontally or vertically, thereby introducing variations in orientation. Rotation entails rotating the image by a certain degree, which simulates different viewing angles. Cropping involves extracting a portion of the image, which can help focus on specific regions of interest. By introducing these modifications, the dataset is expanded with a wider range of perspectives and variations. The augmentation procedure helps to increase the model's capacity to generalize to previously unobserved data and enhances validation accuracy by exposing the model to a more comprehensive set of scenarios and conditions.

Image resizing is employed to standardize the size of the endoscopy images to 256x256 pixels and 3 color channels (RGB). This operation is crucial for reducing the computational complexity of the deep learning process. Larger images require processing a higher number of pixels, which increases the computational time and complexity. By resizing the images to a uniform size, the computational burden is mitigated, facilitating more efficient processing and analysis by the deep neural network. Uniform image sizes ensure consistency in the input data, which is essential for achieving reliable and reproducible results. The combination of image augmentation and image resizing optimizes the dataset for training and enhances the efficiency of the subsequent classification task. Preprocessing is employed to enhance the quality of the images, ensuring optimal input for subsequent analysis. Feature extraction aims to extract relevant information from the images that can distinguish between cancerous and non-cancerous tissues. Fig. 3 depicts data visualization, facilitating insights into the distribution and characteristics of the data.

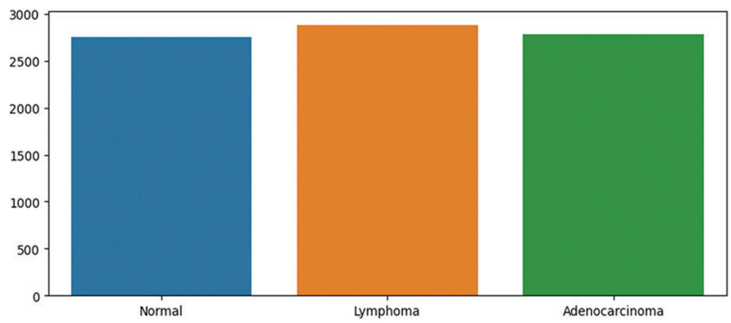

Fig. 3. Data visualization

3.3. QUADRATIC CONVOLUTIONAL NEURAL NETWORK

QNN is a type of neural network architecture specifically designed for image classification tasks [20]. It builds upon the traditional CNN architecture by incorporating quadratic convolutional layers, which introduce additional non-linearity to the network. By applying quadratic filters to the input image, the convolutional layers in a QNN enable the network to identify more intricate patterns and correlations in the data. These quadratic filters enable the network to model non-linear interactions between image features, enhancing its ability to discriminate between different classes.

QNNs typically include pooling layers, fully connected layers, and activation functions, similar to traditional CNN architectures as shown in Figure 4. The use of quadratic convolutional layers distinguishes QNNs from standard CNNs, offering potentially improved performance for certain image classification tasks. However, training and optimizing QNNs may require additional computational resources and careful parameter tuning due to their increased complexity compared to traditional CNNs.

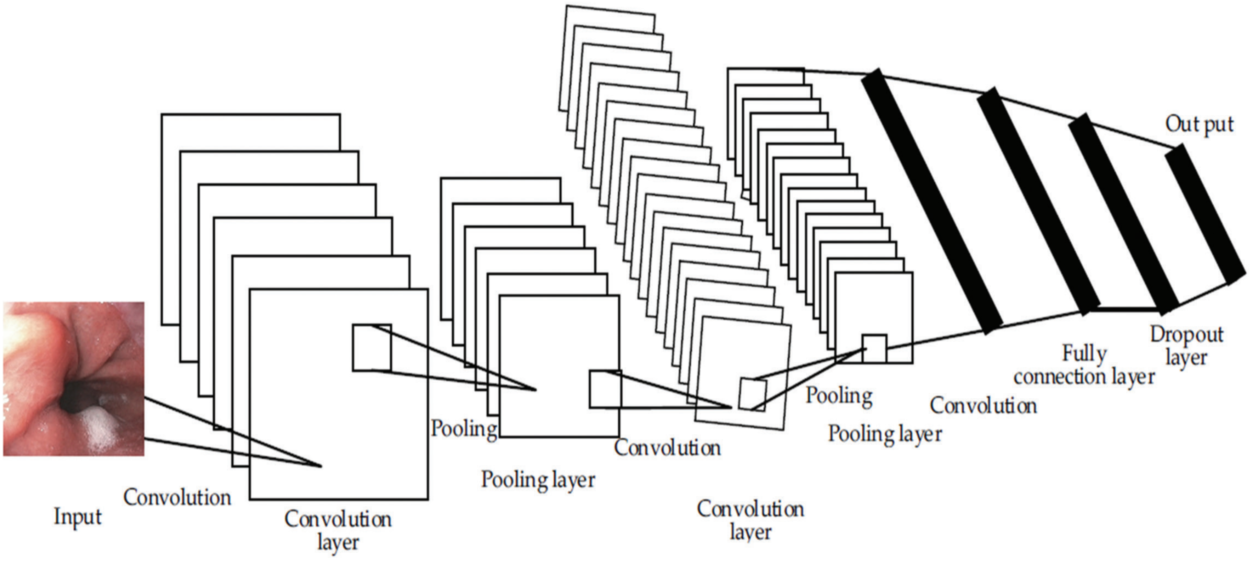

Fig. 4. Architecture of the QCNN model

The input vector be S^t with dim as dimension and the transpose be $\{\}^t$. Linear function of the neuron be

$$F(S)=WS+B \tag{1}$$

Weights are represented by $W=\{w_1, w_2,,,,,,w_{dim}\}$ and the bias be 'b'.

A quadratic function for a neuron can be described as a mathematical expression that incorporates quadratic terms, representing a non-linear relationship between the neuron's input and output.

$$Q(S)=S'^t\, W_q\, S' \tag{2}$$

S'^t denotes the augmented vector represented by $S'^t=\{S^t \mid 1\}=\{s_1, s_2,,,,s_{dim},1\}$ and the weights are

$$\text{Weight}_C = \begin{bmatrix} W'_{1,1} & W'_{1,2} & . & . & W'_{1,\dim+1} \\ W'_{2,1} & . & . & . & . \\ . & . & . & . & . \\ W'_{\dim,1} & . & . & . & W'_{\dim+1,\dim+1} \end{bmatrix} \tag{3}$$

For image classification, we construct networks using a mix of quadratic and linear neurons, with the convolutions layers created utilizing linear neurons for later stages of classification, and quadratic neurons are employed for extracting picture representation. Two factors guided the decision: first, the network can learn complicated representations when higher-order functions are used to extract picture data; second, the kernel size restricts the neurons' input dimension, resulting in networks with manageable parameters.

Let $S_{m,n}{}^t=\{s_1, s_2, ,,,s_{N^2}\}$ represent the pixels in the image's receptive field that the kernel spans at position (m,n). Next, the quadratic neuron's output is calculated as

$$QD(S_{m,n}) = S'^t_{m,n}\, W_q\, S'_{m,n} \tag{4}$$

A quadratic kernel has $P(n^2+1)^2$ parameters, while a CNN layer with linear neurons made up of P kernels of size $n\times n$ has $P(n^2+1)$ parameters; however, n is typically limited to smaller values (1, 3, 5). thereby making it possible for us to construct quadratic networks with a controllable rise in the number of parameters.

3.4. EXTREME LEARNING

Extreme Learning begins by randomly initializing the input weights and biases of the hidden neurons. These weights and biases are typically drawn from a random distribution. Once the parameters are initialized, the algorithm proceeds with forward propagation.

Given an $N \times P$ sized data matrix (X)where P is the number of samples, the hidden layer output (H) is computed using a non-linear activation function (g(.)). Mathematically, this can be expressed as:

$$H=g(W\cdot X+b) \tag{5}$$

$W\cdot X$ represents the weighted sum of inputs to the hidden layer, and g(.) is typically a sigmoid, tanh, or ReLU function applied element-wise. Following the computation of the hidden layer output, ELM proceeds to compute the output weights(B) using a linear regression approach. This is achieved by solving a linear system, expressed as:

$$B = H^{+}.T \tag{6}$$

where H^{+} is the Moore-Penrose pseudo-inverse of Hand Tis the target output matrix. In matrix notation, this equation can be represented as:

$$B = (HT.H)^{-1}\, H^{T}.T \tag{7}$$

Fig. 5 presents a flowchart depicting the Extreme Learning process, outlining the sequential steps involved in implementing this technique.

ELM offers a streamlined approach to training neural networks. By randomly initializing the input weights and biases and utilizing a fixed, single hidden layer, ELM achieves fast training speeds, particularly advantageous for large datasets. Despite its simplicity, ELM's performance hinges on the quality of randomly chosen parameters and the representativeness of the training data.

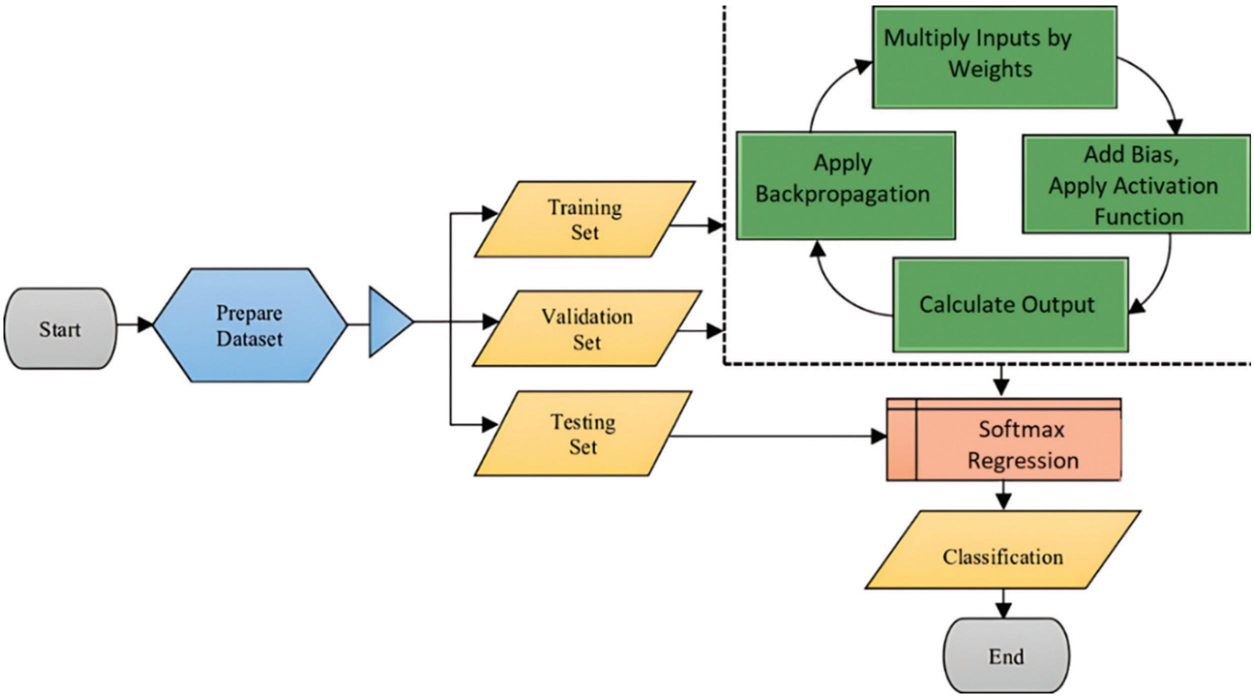

Fig. 5. Flowchart of Extreme learning

3.5. PROPOSED ARCHITECTURE

The proposed research introduces a novel system for identifying and classifying gastric cancer from stomach endoscopy images, employing deep learning techniques. Three primary steps make up the methodology: feature extraction, classification, and preprocessing. Pre-processing is the process of improving the endoscopic image quality in order to make further analysis easier. Feature extraction aims to derive meaningful characteristics from the images, representing the disease-affected regions effectively. These features serve as inputs for training and testing the classification model, which is pivotal in accurately categorizing the presence and type of gastric cancer in the images. Fig. 6 displays the proposed model architecture for gastric cancer classification.

The heart of the methodology lies in the feature extraction process, as it directly influences the efficacy of the classification system. Extracting a large number of features from each image could lead to computational inefficiencies during classifier training. To address this, QCNN is proposed as the classifier. However, QCNNs typically demand vast amounts of training data, which may not always be readily available, especially in the context of gastric endoscopy images. In cases where the dataset is limited, methods such as extreme learning and fine-tuning become valuable for enhancing the classifier's performance.

The dataset comprises gastric endoscopy images from various subjects, encompassing different categories, including two types of cancers and healthy controls. By leveraging this dataset, the proposed methodology aims to train a QCNN framework, updating its parameters using the available training set.

This approach enables the classification system to learn and distinguish between different cancer types and healthy tissue accurately, contributing to improved diagnosis and treatment of gastric cancer. Table 2 provides an overview of the hyperparameters used in the model.

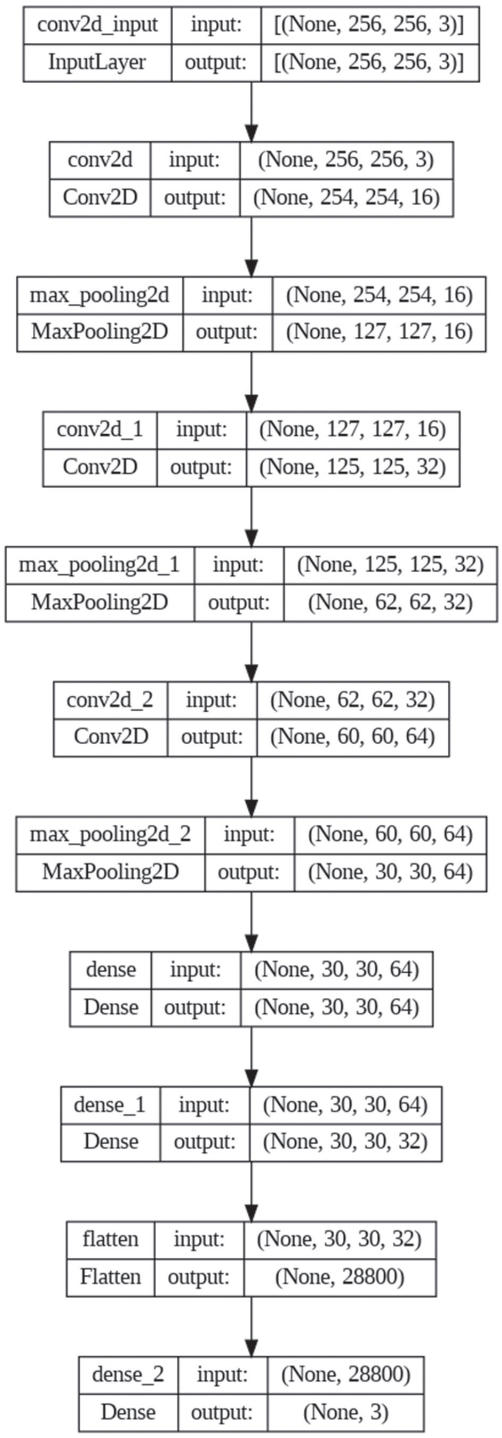

Fig. 6. Proposed model architecture

Table 2. Hyper parameters

Parameters	Values
Optimizer	Adam
Activation Function	Relu, softmax
Loss	Categorical crossentropy
Batch Size	128
Number of epochs	25

3.6. FINE TUNING

Fine-tuning, it is generally accepted that all model layers should be copied, with the exception of the final layer. This new layer should have the same number of neurons as in the new target domains. Fine-tuning a portion of the network, usually the last layer, enables the network to adjust to the characteristics of the target domain, leading to enhanced performance across various classification tasks. This is because the early layers of the network extract features that are applicable to a wide range of image recognition tasks. A detailed overview of the suggested approach for classifying stomach cancer is shown in Table 3.

Table 3. Model summary

Total Parameters	116,227
Trainable Parameters	116,227
Non- Trainable Parameters	0

3.7. HARDWARE AND SOFTWARE SETUP

The proposed study utilized the Google Colaboratory platform in conjunction with the Microsoft Windows 10 operating system to establish a robust computational environment. The modeling process involved the application of the Python programming language, leveraging the Keras package and TensorFlow backend for training. The conceptualized models were specifically configured to accept preprocessed and augmented datasets, ensuring precise decision-making capabilities. To assess the efficacy of the proposed model, evaluate the predictions of the model on the test dataset.

4. RESULT AND DISCUSSION

Performance indicators that are essential for assessing the model's efficacy, especially in classification tasks, include accuracy, recall, precision, and F1-score. Table 4 gives an idea about the performance parameters used in the study. Accuracy is a straightforward metric, often used when the class distribution is balanced. While accuracy offers a view of performance of the model, its adequacy might be limited in scenarios where there is an imbalance in the class distribution.

Accuracy by itself might not be sufficient to fully comprehend a model's performance, particularly in cases of imbalanced datasets in which one class predominates over the other. Contrarily, precision calculates the percentage of accurate positive predictions made out of all positive forecasts.

Recall quantifies the percentage of real positive cases among all actual positive cases that the model correctly identifies as true positives. It aids in determining how well the model is able to locate every positive occurrence without overlooking any. When false negatives are expensive, recall becomes crucial. The f1-Score provides a balance between precision and recall by taking the harmonic mean of these two criteria. It is particularly helpful in cases of unequal class distribution. F1-Score is a more accurate indicator of a model's overall performance, particularly in situations where the class distribution is not uniform or when simultaneous optimization of precision and recall is required. Table 5 provides a comprehensive classification report for the system.

Table 4. Performance parameters

Parameters	Equation
Accuracy	(TP+TN)/(TP+TN+FP+FN)
Precision	(TP)/(TP+FP)
Recall	(TP)/(TP+FN)
F1-Score	2*(Precision*Recall)/ (Precision+Recall)
TP=True Positive TN=True Negative FP=False Positive FN=False Negative	

Table 5. Classification report for the system

	precision	recall	f1-score	support
Adenocarcinoma	0.98	0.96	0.97	522
Lymphoma	0.93	0.94	0.93	590
Normal	0.93	0.94	0.93	572
accuracy			0.94	1684
macro avg	0.95	0.95	0.95	1684
weighteg avg	0.95	0.94	0.94	1684

An accuracy plot of a proposed system displays the performance of the system over different iterations, epochs, or other training iterations. It shows how the accuracy of the model evolves during the training process. As shown in Fig. 7, the x-axis usually represents the number of iterations or epochs, while the y-axis represents the accuracy achieved by the model on the training or validation data. This plot is essential for understanding how well the proposed system learns from the data over time. It helps in diagnosing potential issues such as overfitting or underfitting.

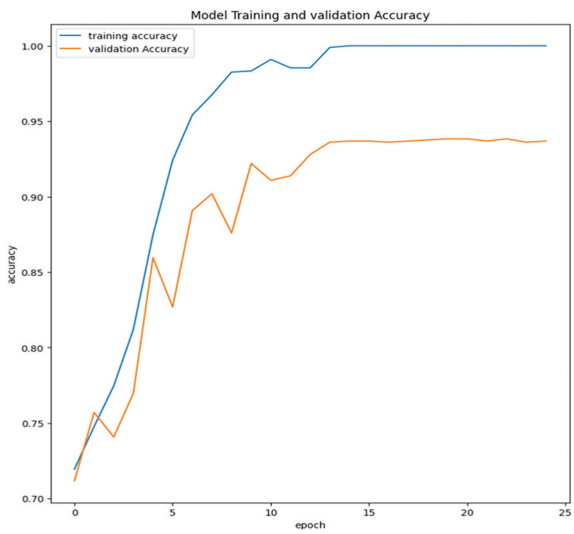

Fig. 7. Accuracy plot of the proposed system

A loss plot of a proposed system illustrates how the loss function decreases (or increases) over the course of training epochs or iterations, as shown in Fig. 8. The loss function quantifies how well the model is performing; typically, lower values indicate better performance. During the initial stages of training, the loss is typically high as the model's parameters are randomly initialized, and it makes random predictions. As training progresses, the model adjusts its parameters to minimize the loss, aiming to improve its predictions. The loss plot should show a decreasing trend over time. Fluctuations in the loss values may occur due to various factors such as the complexity of the dataset, learning rate, and batch size.

Monitoring the loss plot is crucial for assessing the training progress and diagnosing potential issues like overfitting or underfitting.

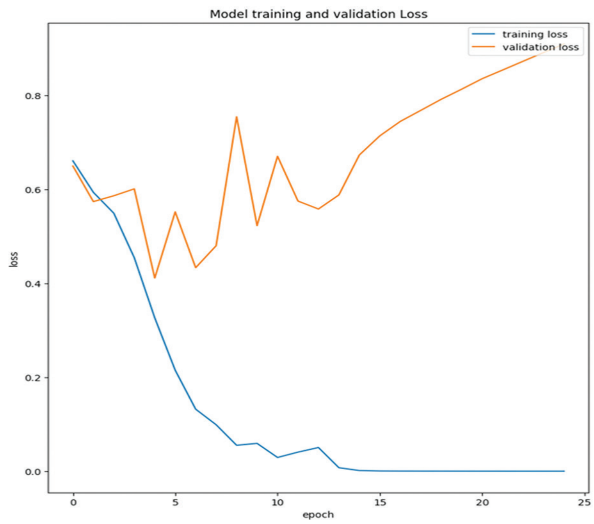

Fig. 8. Loss plot of the proposed system

As seen in Fig. 9, the confusion matrix offers a thorough analysis of the right and wrong predictions the model made on a dataset. In the confusion matrix, it is demonstrated that 501 adenocarcinoma images were correctly classified as adenocarcinoma, 552 lymphoma images were correctly classified as lymphoma, and 538 images were correctly classified as normal.

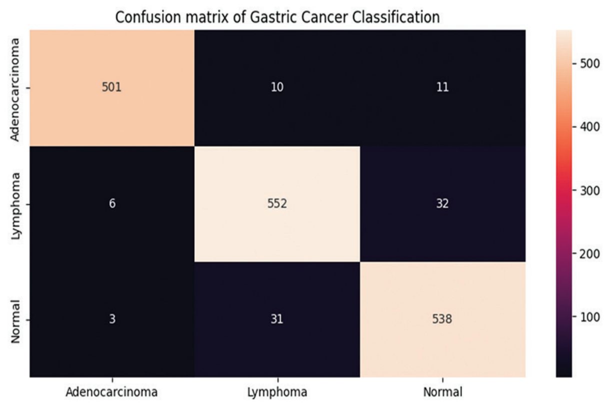

Fig. 9. Confusion matrix of the proposed system

Fig. 10 illustrates the classification output of the proposed gastric cancer classification system, showcasing the model's predictions for a sample set of endoscopy images.

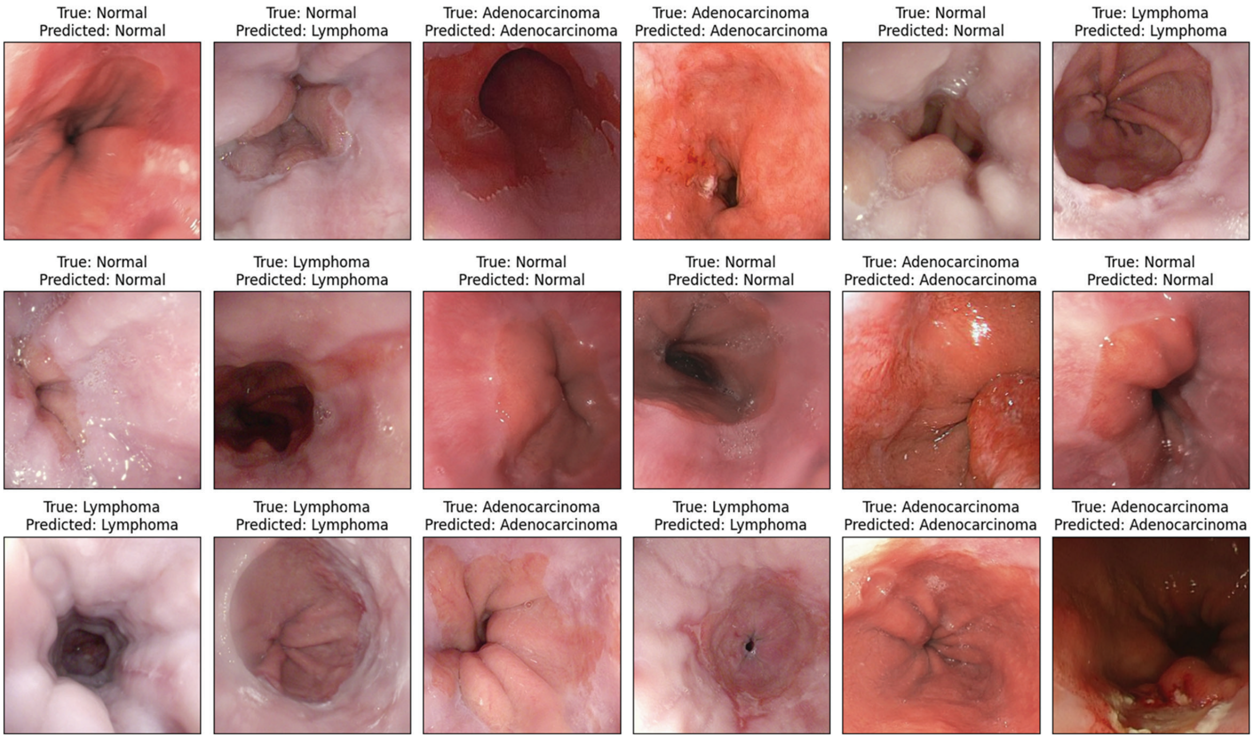

Fig. 10. Classification output of the proposed system

Table 6. A comparison between the suggested system and existing methods

Sl No	Author & Year	Methodology	Accuracy
1	Gong et al [23]	Deep learning based clinical decision support system	81.5 %
2	Yao et al [27]	YOLO	85.15 %
3	Du et al [22]	ENDOANGEL-MM	86.54 %
4	Zhou et al [24]	EfficientNet	88.3 %
5	Li et al [26]	Deep learning based ENDOANGEL-LA	88.76 %
6	Liu et al [21]	2 DCNN	90.8 %
7	Jin et al [25]	Mask R-CNN	90.25 %
	Proposed System		**94 %**

5. CONCLUSION

With gastric cancer ranking as the fifth most frequent cancer globally, cancer continues to pose a serious threat to global health. Accurate classification is essential for effective treatment strategy and improving patient outcomes. The study presents a novel approach utilizing a QCNN combined with extreme learning and fine-tuning techniques for the classification of gastric cancer from stomach endoscopy images. The proposed methodology achieves an impressive accuracy of 94% through extensive experimentation and validation on a comprehensive dataset comprising gastric cancer images. The results demonstrate the effectiveness and potential of the approach for gastric cancer classification. By leveraging QCNN architecture specifically designed to capture intricate patterns and features within medical imaging data, with a fine-tuning technique to enhance generalization capability, the model delivers robust performance. The technique of concatenating QCNN structures with extreme learning proves to be efficient in achieving peak classification rates. The developed QCNN model holds significant promise for assisting clinicians in accurate diagnosis and personalized treatment strategies, ultimately contributing to better patient outcomes in the fight against gastric cancer.

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