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Intelligent System for Celiac Disease Detection Based on Deep Learning

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Abstract— In this study authors explore the application of deep learning techniques for the early detection of celiac disease through the analysis of medical imaging and clinical data. We used the convolutional neural networks (CNNs). The proposed model exhibits promising accuracy in identifying patterns indicative of celiac disease from diverse images of a big database. The integration of deep learning in celiac disease diagnosis holds the potential for enhancing early intervention and improving patient outcomes, marking a significant advancement in medical diagnostics. The proposed approach elucidates the intricacies of celiac disease and implements a robust Convolutional Neural Network (CNN) model for accurate image classification. Achieving an average accuracy of 96%, this method promises enhanced diagnosis and management, paving the way for personalized healthcare interventions with significant improvements in patient outcomes and quality of life.

Keywords— *Medical diagnostics, Image processing, Celiac detection, CNN*

1. INTRODUCTION

A significant portion of celiac disease (CD), which has been increasing globally, goes untreated. To close the gaps in timely detection and management, new approaches are needed.

Over the past ten years, artificial intelligence (AI) has grown exponentially on a global scale. With the advent of big data and powerful computational ability, we now have self-driving cars and smart devices in our daily lives. Huge databases in the form of electronic medical records and images have rendered healthcare a lucrative sector where AI can prove revolutionary. It is widely utilized to get around obstacles in healthcare workflows.

It can be used in a variety of ways, such as screening tools, diagnosis, the creation of new therapeutic drugs, management plan proposals, prognostic indicator definition, etc. We review the areas where it may augment physicians in delivering better healthcare by summarizing current literature on the use of AI in healthcare using CD as a model [1].

Electronic versions of medical data used for clinical practice have become widely accessible in recent years. With the ultimate goal of customizing each patient's evaluation and treatment plan, these data help clinicians make decisions about patient care. Using various data modalities, such as genomic data, electronic medical records (EMR), textual data (like unstructured patient notes), and image data (like CT scans, MRIs, and endoscopies), to improve and customize a patient's therapy is, in fact, the aim of "precision medicine." Practitioners have used algorithmic techniques from machine learning (ML), a rich area of artificial intelligence, to model

this vast amount of data. The basic idea behind ML is to use an algorithmically learned function from a huge corpus of examples to map a set of inputs to a set of outputs. Deep learning (DL) techniques have gained popularity recently, whereas machine learning (ML) techniques have traditionally depended on specialized domain knowledge and manually created features [1].

By quickly detecting celiac disease and avoiding the time, effort, and costs involved with a delayed diagnosis, the goal of developing a deep learning system for the condition's detection is to reduce patient suffering. To improve patient well-being, this effort entails collecting medical data, preprocessing the data, training a deep learning model, and evaluating its effectiveness [2].

Deep learning has become a popular and cutting-edge technique for complex computer vision applications due to the abundance of processing power. Research on celiac disease may benefit from deep learning in several ways, including diagnosis and classification. Based on visual cues, deep learning algorithms can be trained on medical images (such as endoscopic or histopathology images) to help diagnose and categorize celiac disease [3].

Because undetected celiac illness costs an average of \$3,964 more than healthy people, we have decided to use AI to detect celiac disease early and lessen the burden on patients [3].

The inability to distinguish between micronutrients depending on nutrients, particularly minerals, and vitamins, is a result of celiac disease. This results in a deficiency of nutrients, which raises the risk of illnesses brought on by malnutrition-induced weight loss [4].

However, we have implemented the requirement that everyone experiencing celiac disease symptoms assess the situation right away and get examined. We selected the proposal's concept to help physicians by analyzing the patient's intestines and training the device to differentiate between healthy and sick intestines so that the gadget can identify the outcome on its own [5].

This manuscript's remaining sections are organized as follows: A bibliographic analysis of recent related works is presented in the second part. After that, the steps of the suggested method are described. In section four, researchers explain all the experimental results achieved after the development of the proposed system. The last section is the conclusion of the manuscript.

2. RELATED WORK

Gluten, a protein included in wheat, rye, and barley, causes an immunological reaction that harms the lining of the small intestine in people with celiac disease, an autoimmune

condition. People with celiac disease must strictly adhere to a gluten-free diet to manage their condition because this damage can cause a variety of gastrointestinal and systemic symptoms.

Recent years have seen a surge in studies on the effects of celiac disease on people of all ages, its sensitivity to wheat proteins like gluten, and the use of deep learning in healthcare for precise diagnosis. Examine in-depth many current relevant works that are concerned with the identification of celiac disease. Examples of bibliographic research are shown in Table 1.

difficulty is that new and more effective detection and management techniques are required.

Since CD is becoming more common, new detection techniques are needed, and artificial intelligence (AI) is leading the way in healthcare transformation by using AI-driven solutions to improve clinical processes and patient care in CD diagnosis and management.

An effective method for identifying celiac disease in a large database of intestinal biopsies is shown in the proposed work. The successive processes of our system are depicted in Fig 1.

Table.1 Some works of the state of the art.

Ref.	Description of Database	Techniques	Results
[6]	63 video capsule endoscopy (VCE)	Using an unbiased VCE scoring tool	They assessed the ability of machine learning to grade disease severity in CeD quantitatively.
[7]	Collected endoscopy images from 18 CD patients and 16 non-CD controls.	Applied (ML) and (DL) algorithms on images for the detection of villous atrophy (VA) using (CNN)	They provide an accurate algorithm for automated detection of mucosal changes associated with VA in CD patients.
[8]	The data set consists of 109 films	Using the right filters, the proper diagnostic can be obtained by image processing.	Demonstrate that a diagnosis of celiac disease is possible with a computer.
[9]	It consists of endoscopic images of the small bowel and clinical parameters.	Using endoscopic images through a deep learning approach	The results show that additional clinical parameters can improve classification accuracy.
[10]	Based on a pediatric cohort of 124 patients with CD.	They chose a deep learning-based methodology for image analytics	Generate a highly accurate predictive tool for complex gastrointestinal diseases, using CD.
[11]	Dataset obtained from Olympus flexible endoscope EVIS EXERA III (GIF-H190)	Synthetic Minority Oversampling Technique Sobel Operator Discret Wavelet Transform High Order Spectral Balanced Random Forest Classifier	Accuracy rate : 89.41% Precision rate : 94.23% Recall : 89.09%
[12]	50 individuals including 16 males and 34 females in average age of 32	10-fold Cross Validation used for training the model K-Nearest Neighbor Support Vector Machine Naïve Bayes Random Forest Classifier Decision Tree	Accuracy rate : 80% Precision rate : 100% Recall : 88%
[13]	ImageNet Database includes 100 types of objects with more than 1000000 images of size 224*224*3	Convolutional Neural Network	Accuracy rate : 99.7% Precision rate : 99.6% Recall : 99.3%

3. DESCRIPTION OF THE PROPOSED APPROACH

Worldwide, the prevalence of celiac disease has been rising, and a sizable percentage of cases go undetected. The

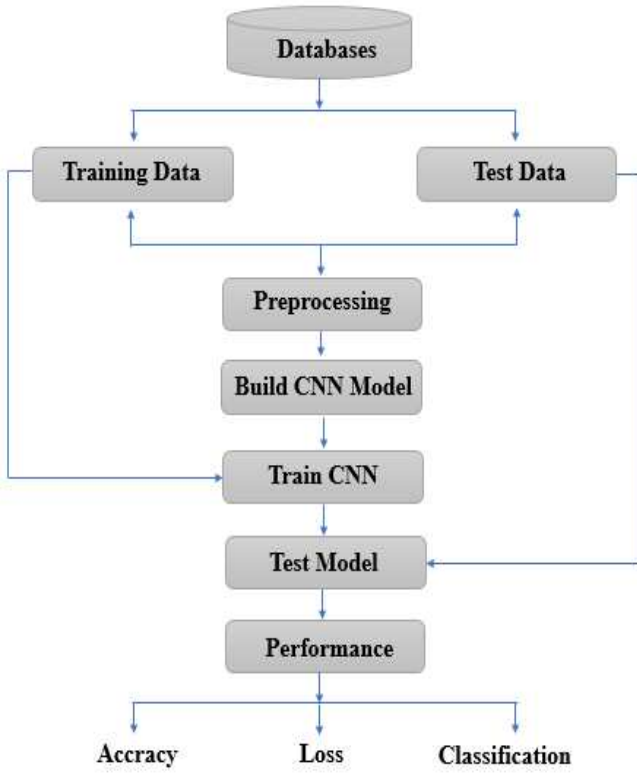


Fig.1 Flowchart of the proposed system

3.1 Description of the databases

The database is used as images for diagnosing small intestine celiac disease by endoscopic imaging. It contains 37,790 classified images stored using the jpg format. 14, one case represents a healthy person, and the rest represents a disease case [14]. Fig 2 shows some samples of the database.

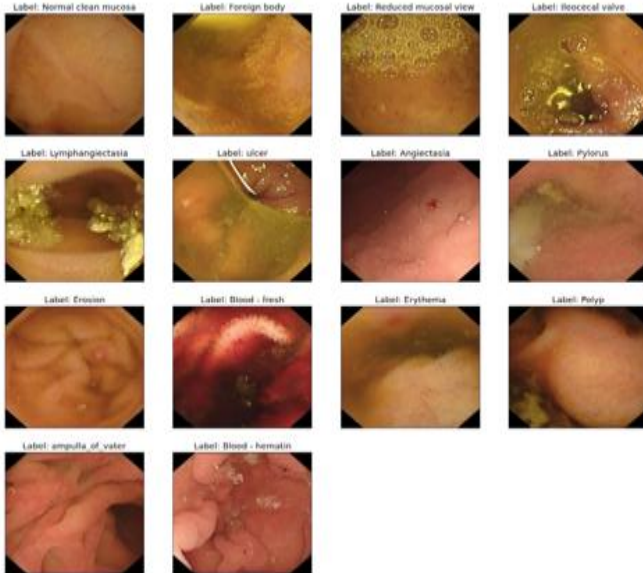


Fig.2 Example of celiac disease database images

3.2 Data Processing

The presented database contains information about image paths and diagnostic status. Moreover, statistics were displayed regarding the number of images for each category.

It presented 14 categories of infected intestines as mentioned in Fig 3.

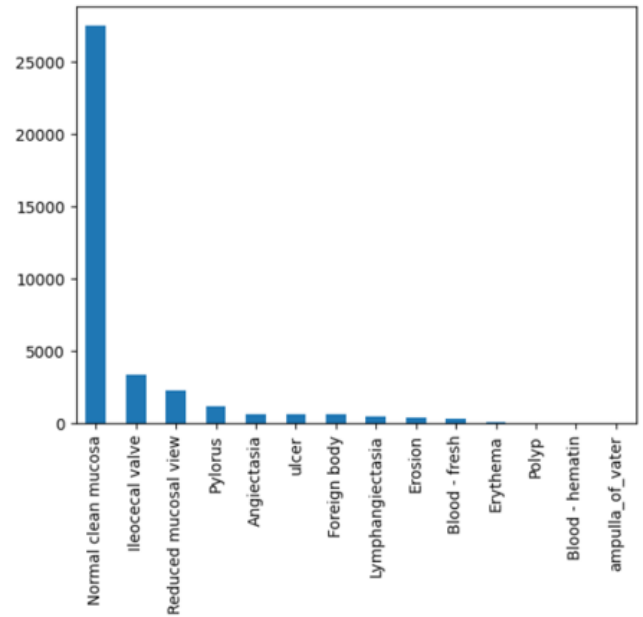


Fig.3 Database statistical distribution for each disease diagnosis

3.3 Deep learning

Neural networks having three or more layers are used in deep learning, a subset of machine learning. To enable the human brain to "learn" from vast volumes of data, these neural networks attempt to replicate certain features of its activity. Additional hidden layers can significantly improve optimization and accuracy, even if a single-layer neural network can only make rough predictions [15].

Deep learning has an impact on a range of artificial intelligence services and applications, allowing for automation and the completion of physical and analytical activities without the need for human participation. Digital assistants, voice-activated TV remote controls, and credit card fraud detection are just a few of the commonplace goods and services that rely on deep learning technology. Additionally, it is essential to develop technology like autonomous vehicles [15].

The Convolutional Neural Network (CNN) is the foundation of the suggested method.

CNNs are made to handle tasks that require grid-like data, such as pictures and movies. They are frequently employed in computer vision and image identification tasks, and they employ convolutional layers to automatically learn spatial hierarchies of features [16]. Fig 4 displays the model's sequential architecture.

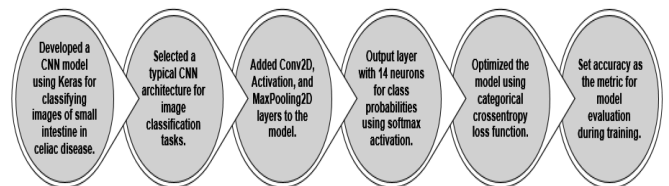


Fig.4 Sequential architecture of the used model

3.3.1 Building and training CNN

The specified CNN model is built to be trained on the previously selected features, and the number of training times is 20.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 30, 30, 64)	1792
activation (Activation)	(None, 30, 30, 64)	0
max_pooling2d (MaxPooling2D)	(None, 15, 15, 64)	0
conv2d_1 (Conv2D)	(None, 13, 13, 128)	73856
activation_1 (Activation)	(None, 13, 13, 128)	0
max_pooling2d_1 (MaxPooling2D)	(None, 6, 6, 128)	0
flatten (Flatten)	(None, 4608)	0
dense (Dense)	(None, 64)	294976
activation_2 (Activation)	(None, 64)	0
dense_1 (Dense)	(None, 32)	2080
activation_3 (Activation)	(None, 32)	0
dense_2 (Dense)	(None, 14)	462
activation_4 (Activation)	(None, 14)	0

Total params: 373166 (1.42 MB)
 Trainable params: 373166 (1.42 MB)
 Non-trainable params: 0 (0.00 Byte)

Fig.5 CNN Layers

We developed a CNN model to classify images of the small intestine of people with celiac disease using the Keras library, which is one of the most important tools for preparing a deep learning model for training. A typical CNN architecture suitable for image classification tasks was selected from pre-trained models.

A Conv2D layer and two other Activation and MaxPooling2D layers were added to the Neural Network model using the Keras/TensorFlow library (Fig 5). A Conv2D layer with 64 filters was added, the kernel size is (3, 3), and the input shape size is (32, 32, 3), where (32, 32) means the image size and 3 refers to the number of channels of the image (RGB). Then we added the Activation layer with the ReLU (Rectified Linear Unit) activation function, which is a famous function commonly used in the internal layers of deep neural networks. MaxPooling2D, with a pool size of (2, 2), reduces the image size by providing the largest pixel value in the filter area. This helps reduce the number of parameters and training time and helps the model learn basic patterns.

These layers (Fig 5) are usually used in deep neural networks to gradually learn features from images. The Conv2D layer learns local features in the image, the Activation layer activates the results with the ReLU function, and the MaxPooling2D layer reduces dimensions to reduce model complexity and avoid overfitting.

Convolutional blocks extract features from images, dense layers learn higher-level relationships, and the final softmax layer predicts class probabilities where the output layer is set to 14 outputs that express the diagnostic status of the disease.

3.3.2 Feature Extraction and disease detection

Feature extraction stands as a crucial and indispensable phase after image processing. Here, features are extracted for input into the model, facilitating accurate classification of the respective classes during training.

To evaluate the model, we measure its classification accuracy and loss. Classification accuracy indicates the percentage of correctly classified images, while loss quantifies the disparity between predicted and actual labels. These metrics are crucial for assessing the model's performance in classifying images effectively.

4. EXPERIMENTAL RESULTS

After feature extraction, model building, training using sequential architecture, and applying the optimization function, we proceed to validate the detection. We test the detection for the 14 classes (Fig 6), and the results confirm the accuracy of the detection.



Fig.6 Experimental result for the detection of the 14 symptoms of CD

The model was trained in Google Colab because the data set is large and requires a large processor. We conducted the training process on the training and validation data set. The training process was set to several epochs (20). To monitor the model's performance, the class (tensorboard) was used, which draws curves.

The fitting function was used to train the model, receive training data, number of epochs, and validation data, and select callbacks=[tensorboard_callback] to enable special callbacks and log TensorBoard logs, which helps monitor training progress and improve model performance.

After completing training, the model of the accuracy (Fig 7) and the loss (Fig 8), were displayed for the training and validation data.

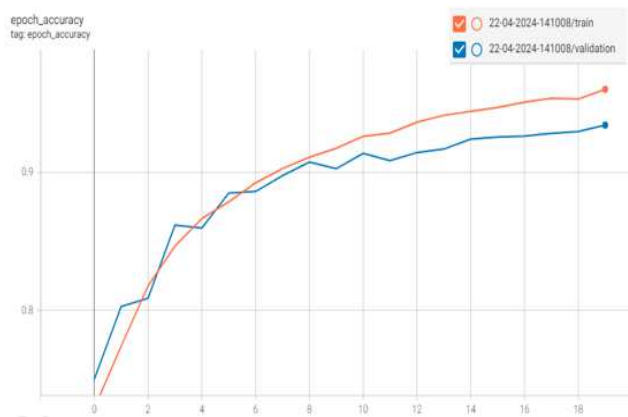


Fig.7 Accuracy for model training and validation

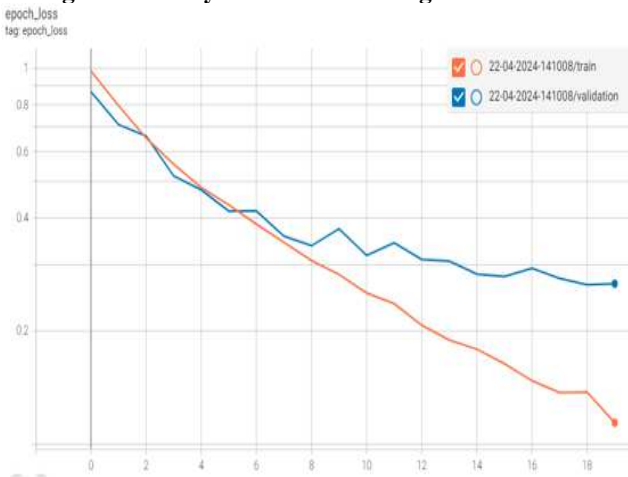


Fig.8 Loss for model training and validation

The figure indicates that the greater the number of epochs, the more accurate the model is in classifying images of healthy and sick people. It also appears that the model's loss function decreases inversely, which makes the model predict with high accuracy and low loss.

Table 2 also shows the performance measure for both accuracy and loss for the model with a different number of epochs.

Table.2 Performance Measures

Epoch	Loss	Accuracy	Val_Loss	Val_Accuracy
5	0.4315	0.8762	0.4258	0.8808
10	0.2237	0.9343	0.3600	0.8970
15	0.1324	0.9596	0.2809	0.9188
20	0.0836	0.9723	0.3003	0.9260

The model's training performance was over 20 epochs, and the accuracy achieved a gradual improvement while reducing the loss, which reflects the improvement in the model's performance as the training process progressed.

We evaluated the model's performance based on the confusion matrix. The Confusion Matrix as presented in Fig 9 is a matrix used to evaluate the performance of the classification model by comparing the actual classifications. With the classifications that the model predicted, it receives the original test data outputs and the prediction outputs.

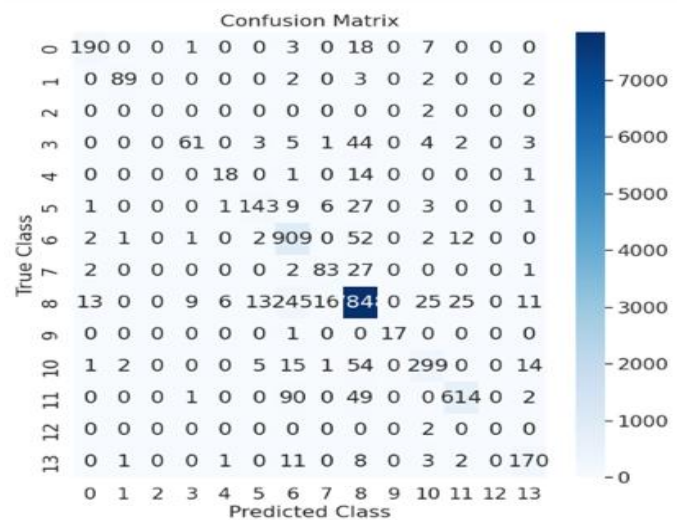


Fig.9 Confusion Matrix distribution of the correct prediction model for the 14 classes

The main diagonal of the matrix shows the distribution of the correct prediction model for the 14 classes.

Category 8 (Fig 10), which represents the healthy state of the small intestine of people, shows that its prediction rate is large concerning the dependent data, as a result of the low percentage of correct predictions in it with the lowest accuracy.

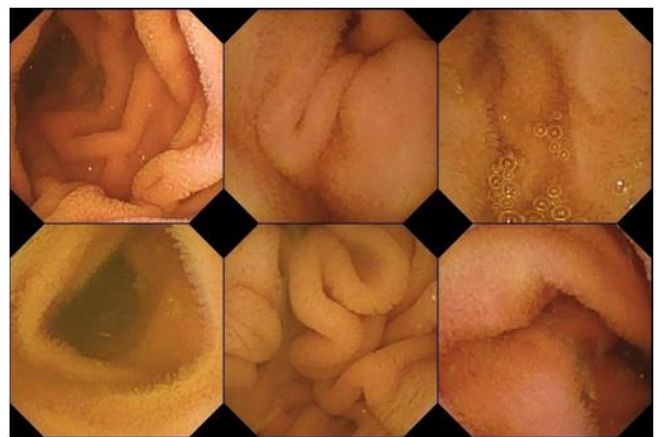


Fig.10 Category8, Normal clean mucosa

We loaded the trained model from a specified file ('modelpro.h5') using the load model function from Keras. In addition to downloading a dictionary containing an index of the classes that represent diagnostic cases (class indices) from the file ('vocpro.class_indices.pkl'), this dictionary is used to convert the digital index of classes into class names.

After that, we developed a user interface using tkinter, a Python library for creating a GUI, a file dialog for selecting files, and a message box for displaying messages if it is normal as Fig 11 or infected as Fig 12, Fig 13, Fig 14, Fig 15 and Fig 16.

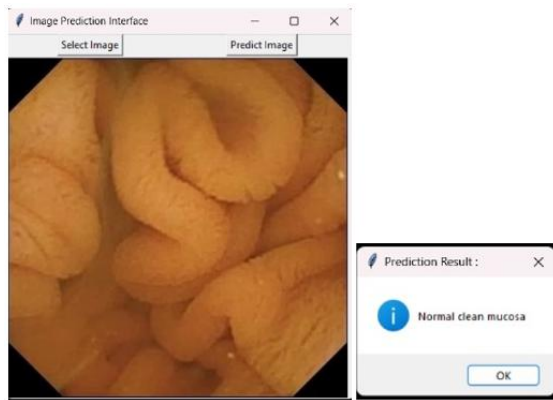


**Fig.11 Image prediction interface with prediction result
Normal clean intestine**

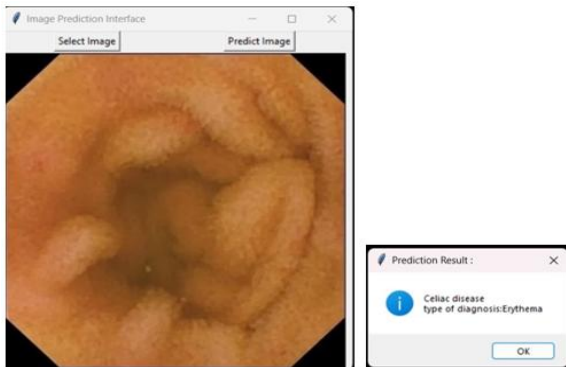


**Fig.12 Image prediction interface with prediction result
Celiac disease type of diagnosis: Erythema**

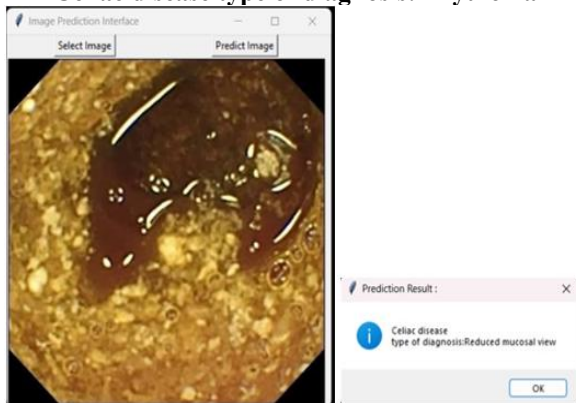


**Fig.13 Image prediction interface with prediction result
Celiac disease type of diagnosis: Reduced mucosal view**

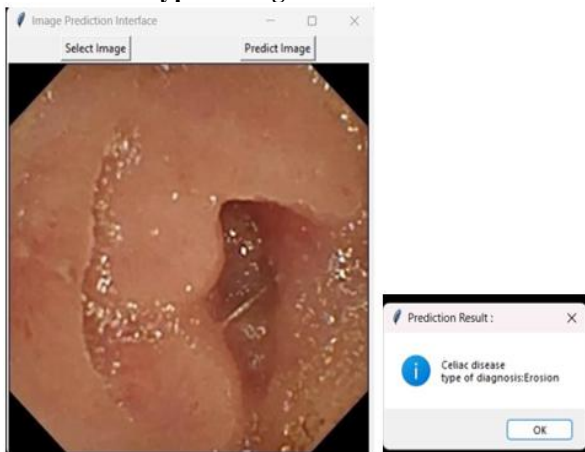


**Fig.14 Image prediction interface with prediction result
Celiac disease type of diagnosis: Erosion**

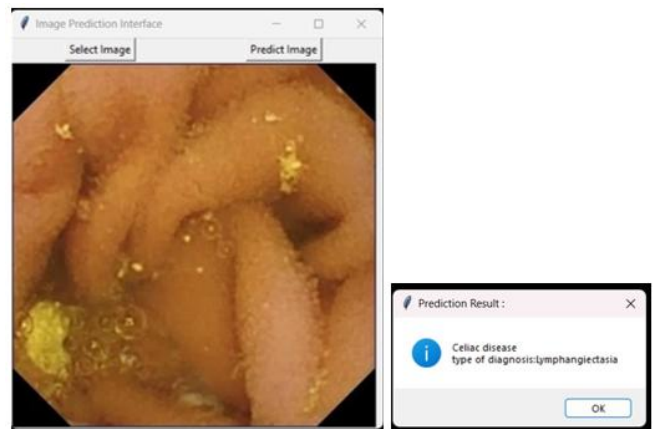


**Fig.15 Image prediction interface with prediction result
Celiac disease type of diagnosis: Lymphangiectasia**

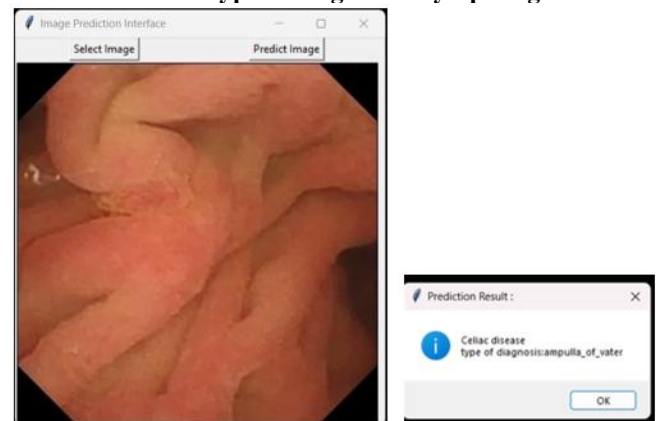


**Fig.16 Image prediction interface with prediction result
Celiac disease type of diagnosis: ampulla_of_vater**

5. CONCLUSION

Through the practical implementation of deep learning models trained on a large dataset, coupled with the development of user-friendly interfaces, the proposed approach demonstrates promising results in accurately classifying images of the small intestine and predicting diagnostic outcomes, achieving an average accuracy of 96% and demonstrating a good balance between precision and recall in class classification. These findings underscore the potential of innovative technological solutions to positively impact the diagnosis and management of Celiac Disease, paving the way for more effective and personalized healthcare interventions and promising improved outcomes and quality of life for affected individuals.

Availability of data and material: The data is available upon request from the corresponding author.

Declaration of competing 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.

Data availability: Data will be made available on request.

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