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Evaluation Study for Celiac Disease Diagnosing by using Deep Learning Techniques

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ABSTRACT: Consumption of gluten causes the immune system in people with CD to attack the small intestine. Generally, conventional approaches to diagnostics are both expensive and require too much time. This review aims to find out if DL techniques can support the diagnosis and analysis of cancerous tissue through examination of pathology images. To collect our data, we investigated 28 peer-reviewed studies that involved various models like simple ABC-DL models, CNNs, transfer learning methods and MIL. Diagnosis accuracies recorded in studies were 70-100%, demonstrating that AI methods were much more accurate and speedy than those previous used. The report points out the good and bad aspects of modern DL approaches, along with the problems they face concerning labeled data, data accuracy and understanding how the models make decisions. In addition, we mention potential future studies involving multimodal information and making the explanations clearer. This review attempts to cover the latest developments in DL for CD diagnosis and share helpful insights for improving studies in this joint field.

Keywords: Artificial Intelligence, Deep Learning, Computer-Aided Diagnosis (CAD), Celiac Disease.

1. INTRODUCTION

Celiac disease is an enteropathy of the small intestine. It is triggered by exposure to gluten in the diet of susceptible people. The susceptibility is genetically determined. The condition is chronic, and currently, the only treatment consists of permanent exclusion of gluten from the food intake [1][2][3].

CD can occur at any age, from early childhood to elderly, with two peaks of onset, one shortly after weaning with gluten in the first 2 years of life and the other during the second or third decade of life with a preference for females (male/female ratio 1:2). The disease has a variable incidence, with a worldwide prevalence of about 1:100; in Europe is estimated between 0.3 and 1.2% [4][5]. A correct diagnosis of CD requires a precise reconstruction of a puzzle, whose pieces are represented by the clinical, serological, genetic and histological aspects. The evaluation of all these factors, apart from genetics, must take place while the patient is still on a diet containing gluten, since a gluten-free diet changes the clinical, serological and histological pattern, making it impossible to recognize the characteristic aspects of disease. Nonetheless, CD still represents an under-recognized condition, due to heterogeneous symptoms and/or poor disease awareness, and the occurrence of diagnostic delay ranging from 4 to 13 years has been reported by some authors [6]-[11].

The diagnosis of CD can be very challenging, since symptoms can significantly vary from patient to patient and this variability has been compared, not surprisingly, to a chameleon [12]. In 2011, the Oslo Classification ranked the clinical presentation of CD in classical, non classical, subclinical and refractory [13]. The gold standard for CD diagnosis is represented by the combination of both mucosal changes and positivity of serological tests [14] [15].

Despite substantial progress in understanding the pathogenesis of this condition, several areas remain unexplored. These include the diagnostic challenges in heterogeneous presentations, treatment for patients unresponsive to gluten sensitivity, and the utility of serology tests as standalone diagnostics without the need for pathology-based confirmation [16]. Currently, the diagnosis of coeliac disease hinges on serological tests and histological confirmation derived from invasive duodenal endoscopic biopsies [17,18,19]. However, these procedures are invasive, labor-intensive, and time-demanding. Several biopsies are required to achieve sufficient sensitivity for a definitive diagnosis [20,21].

The integration of deep-learning techniques (DLT) in the realm of medical science, particularly within the context of coeliac disease diagnosis and management, has gained significant attention. Deep learning, a subfield of machine learning, has displayed remarkable potential in analyzing complex medical data, including endoscopic images, to discern significant patterns and diagnostic markers [22,23].

The expansive reach of artificial intelligence (AI) has significantly transformed various domains of medical science, extending well beyond the diagnosis of coeliac disease. In cancer diagnostics, AI-enhanced algorithms have been employed to improve prostate cancer detection with some approaches achieving diagnosis accuracies as high as 98% by fusing particle swarm optimization with neural networks [24,25].

Several machine learning and deep learning algorithms have been developed to construct models that make predictions on images. Convolutional neural networks are supervised algorithms that are mostly used for image recognition workloads [26]. Top pre-trained models for image classification are the following: ResNet (Residual Networks), Inception (GoogLeNet), VGG (Visual Geometry Group), EfficientNet, DenseNet (Dense Convolutional Network), MobileNet, NASNet (Neural Architecture Search Network), Xception (Extreme Inception), AlexNet, and Vision Transformers (ViT).

This review will focus on recent research exploring the use of deep learning techniques in diagnosing celiac disease using biopsy images. We will examine various deep learning architectures that have been applied to histopathological image analysis, such as CNNs, as well as the advantages and challenges of using these models in clinical practice. We will also compare the performance of these deep learning models with traditional diagnostic methods, highlighting the potential for deep learning to enhance diagnostic accuracy, reduce diagnostic delays, and provide a more accessible means of diagnosing celiac disease. Additionally, we will explore the challenges and limitations associated with applying deep learning to medical image analysis, including issues related to data quality, model interpretability, and the need for large, annotated datasets for training.

Celiac disease (CD), also known as gluten-sensitive enteropathy or celiac disease, is a long-term autoimmune condition that primarily affects the small intestine and is triggered by the consumption of gluten-containing grains. This section briefly reviews the clinical aspects of CD, its epidemiology, pathophysiology, and the traditional and CAD diagnostic methods used in clinical practice as shown in Figure 1[27].

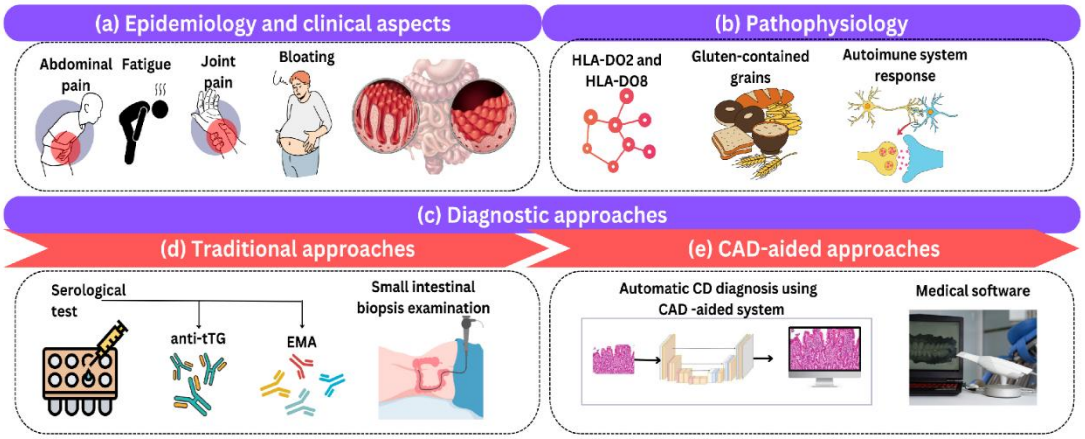

FIGURE 1. - An illustration of (a) epidemiology and clinical aspects, (b) pathophysiology, and (c) diagnostic approaches of CD. Diagnostic approaches include (d) traditional and (e) computer-aided approaches

Many steps are involved in using computers to diagnose celiac disease. Later, info is collected with techniques such as biopsy, endoscopy and clinical tests of the blood. Before using these data, they are prepared by first using methods like ROI detection, binarization and improving contrast. Finally, several algorithms including CNN, K-NN and SVM are used to check if the subject has celiac disease. Figure 2 outlines the entire process.

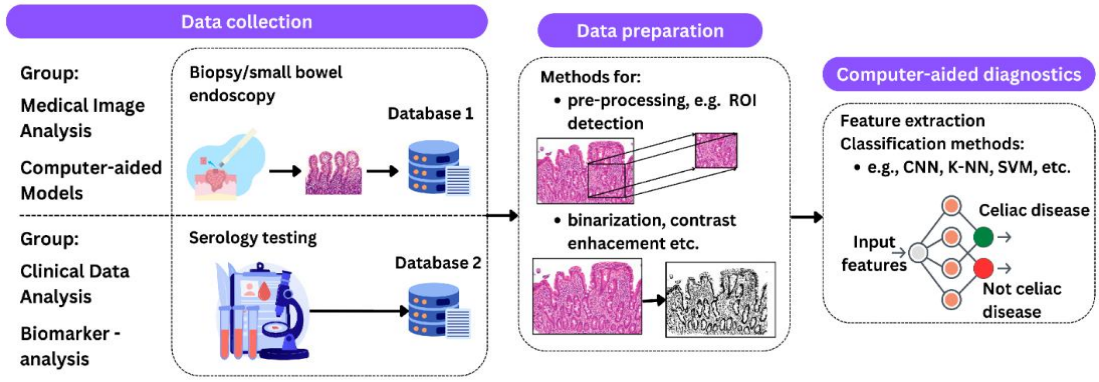

FIGURE 2. - Workflow diagram of computer-aided diagnosis of celiac disease, showing the stages of data collection, preprocessing, and classification using machine learning models. [27]

2. RESEARCH METHODOLOGY

The study reviews recent studies to assess how deep learning methods are applied in detecting celiac disease using biopsy images. As you can see in Figure 1, the process has the following structure:

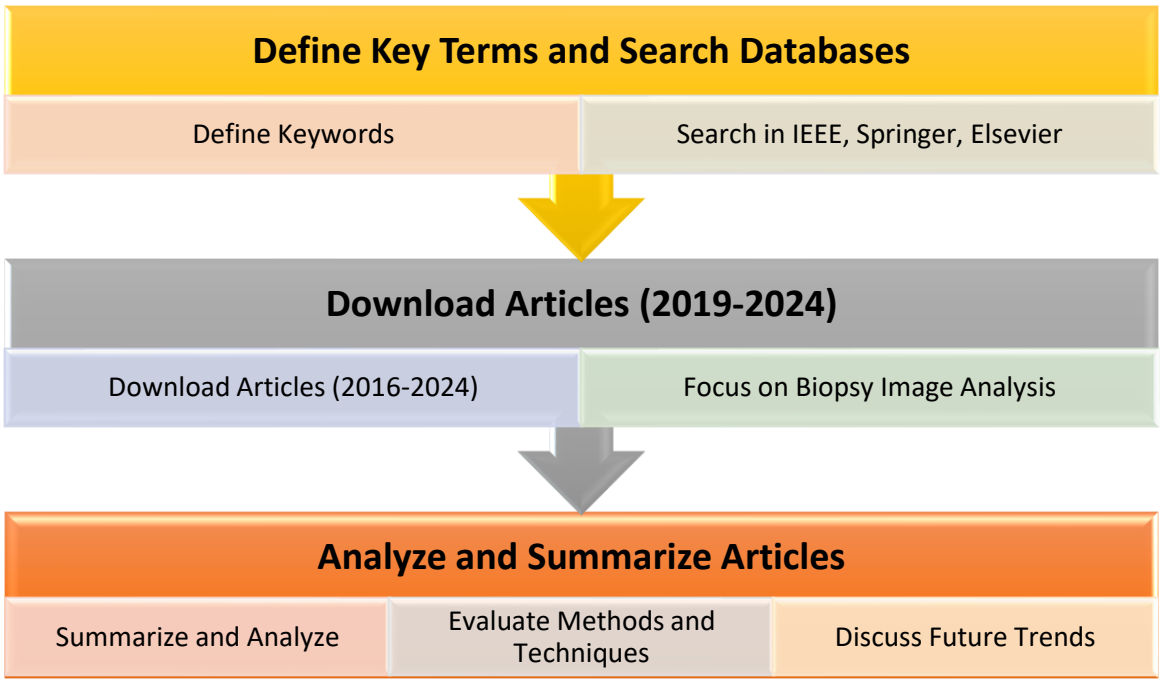

FIGURE 3. - Methodology for the Systematic Process

Designing how you will search for the information.

- At the first stage, a search using keywords was conducted with combinations like:
- "deep learning" AND "celiac disease"
- medical tests using "biopsy images" AND the act of giving a "medical diagnosis"
- The combination of "neural networks" and "biopsy classification"
- "convolutional neural networks" are combined with "histopathology"
- The words were entered into reliable resources such as IEEE Xplore, SpringerLink, Elsevier (ScienceDirect) and Google Scholar, to review papers published from 2019 until 2024.

1.1 WHICH PEOPLE ARE INCLUDED AND WHICH ARE EXCLUDED

For better relevance and quality, the following criteria were placed on research papers:

- Researchers used DL/ML techniques to analyze biopsy or histopathology images for the diagnosis of CD.
- Articles that have gone through the peer-review process in a journal or at a conference
- These novels were written between 2016 and 2024.
- It was originally written in English.
- Results presented in terms of accuracy and sensitivity

The exclusion criteria were:

- Primary research that ignored CD or used different forms of data
- Texts that only discuss traditional machine learning do not include DL.
- Go through review articles, editorials or other works that have not been peer-reviewed.
- Records appearing twice in different databases

1.2 SCREENING

At the start, I looked through 164 different articles. Following the exclusion of extra information and studies beyond the scope, 52 articles remained for consideration. After reviewing inclusion/exclusion criteria, a total of 28 studies relevant to the review were included in the analysis.

The articles I chose were analyzed to find the following information:

- How the study is structured (experimental, comparative and so on)
- These are the characteristics: source, size and image type of the data.
- Technologies and methods from DL/ML have been employed.
- Metrics reported by the models (accuracy, F1-score, etc.)

1.3 ANALYSIS FOCUS

My objective in this review is to study and review different DL and ML models used in diagnosing CD with biopsy pictures. Main focus is placed on architectures such as CNNs, Transfer Learning models (for example, ResNet), Random Forests and Multiple Instance Learning (MIL). Additionally, we assess several issues, including labeling data, interpreting models and data set availability.

According to Table 1, various DL studies have been conducted to detect CDs, yet only a few provide a thorough comparison of their outcomes using different datasets and designs. It addresses the problem by discussing which models offer high dependability and reliability for diagnostics.

Table 1 Studies Related to Deep Learning Techniques in Celiac Disease Diagnosis Using Biopsy Images.

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REFERENCE	TYPE	CASE STUDY	CATEGORY	YEAR	AI TECHNIQUES
[28]	Research Paper	Celiac Disease Image Classification using Convolutional Neural Network	Deep Learning	2024	Convolutional Neural Network (CNN), Transfer Learning (ResNet-18)
[29]	Research Paper	Automated interpretation of biopsy images for the detection of celiac disease using a machine learning approach	Machine Learning	2021	Steerable Pyramid Transform (SPT), Decision Tree, k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), Adaboost, Bagged Trees
[30]	Research Paper	AUTOMATED DETECTION OF CELIAC DISEASE ON DUODENAL BIOPSY SLIDES: A DEEP LEARNING APPROACH	Deep Learning	2019	Residual Convolutional Neural Network (RCNN)
[31]	Research Paper	Diagnosis and Analysis of Celiac Disease and Environmental Enteropathy on Biopsy Images using Deep Learning Approaches	Deep Learning	2020	Color Balancing, Random Multi model Deep Learning (RMDL), Shallow Convolutional Neural Network (CNN), Hierarchical Medical Image Classification (HMIC)
[32]	Research Paper	Exploring Patch-based Deep Learning Approaches for Celiac Disease Diagnosis Using Whole Slide Images	Deep Learning	2022	Convolutional Neural Network (CNN)

[33]	Research Paper	Multiple-instance-learning-based detection of celiac disease in histological whole-slide images	Deep Learning	2022	Convolutional Neural Networks (CNN), Multiple Instance Learning (MIL)
[34]	Research Paper	Precision medicine and machine learning towards the prediction of the outcome of potential celiac disease	Machine Learning	2021	Random Forests, Extremely Randomized Trees, Boosted Trees, Logistic Regression

3. CELIAC DISEASE DIAGNOSIS AND DEEP LEARNING

Over the recent years, progress in the fields of AI has especially in deep learning has caused success in the analysis of medical images thereby raising diagnostic precision and speed. In diagnosing celiac disease (CD), the standard practice today is to visually analyze duodenal mucosal biopsies. When transferred into the diagnostic process, deep learning methodologies can aid pathologists by detecting CD-related abnormalities in biopsy pictures.

For example, Wei et al. designed a deep learning system for CD identification from duodenal biopsy image. With further work, the model based on a residual convolutional neural network provides the residual predictions of patches of duodenal tissue and combines these to generate residual feature vectors for whole-slide classification. In another independent set of 212 images, the model distinguished celiac disease, normal tissue, and nonspecific duodenitis with 93/95 percent, 91/90 percent, and 92/89 percent, respectively. For evaluating all classes AUC was more than 0.95 reveals the good performance for detecting the celiac disease on the biopsy slides [29].

A research done by Kowsari et. Al also designed the CNN model to classify duodenal biopsy images of CD, EE and healthy subjects. When tested on a set of 1000 biopsy images, the CD = 0.99, EE = 1.00, and the HC = 0.97 in terms of the area under the ROC curve. These results provide strongly evidence of discriminative power of the proposed model in discrimination between duodenal biopsies [31].

In addition, Sali et al conducted a systematic review on fairly recent and novel application of deep learning in precision diagnosis of celiac disease. The review anticipated that deep learning models have been trained for the diagnosis of celiac disease on duodenal biopsy images attaining an impressive accuracy in differentiating CD, normal tissues, and nonspecific duodenal inflammation. These models employ the best residual CNNs for the assessment of tissue patches and combine their outputs for whole-slide staging, improving diagnostic accuracy and speed [35].

Applying deep learning for the analysis of biopsy images and development of diagnostic criteria, the celiac disease diagnosis speed would increase, and correct treatment would be prescribed to the sufferers.

4. THE MAIN DEEP LEARNING TECHNIQUES USED FOR CELIAC DISEASE DIAGNOSIS BASED ON BIOPSY IMAGES

Real transformation in identification of diseases through analyzing medical images especially biopsy images is brought about by Deep learning especially CNNs has been prominent in diagnosing of celiac disease (CD). There is vast research evidenced by deep learning to automate the analysis of histopathological images with a goal of detecting certain features which can suggest the presence or intensity of the disease. The diagnosis of celiac disease involves analysis of biopsy images, and more specifically the images of the duodenal tissues. By employing CNNs for segmentation and classification of such images, possible celiac-related changes such as villous atrophy and crypt hyperplasia – the two pathologic hallmarks of the disease [30] can be accurately determined.

4.1 CONVOLUTIONAL NEURAL NETWORKS (CNNS) IN CELIAC DISEASE DIAGNOSIS

Convolutional Neural Networks (CNNs) are a class of deep neural networks that have been developed with a capacity to deal with data in a grid like structure. There are alternating convolutional and pooling layers and it makes the system able on its own to identify the pattern within the input. In medical image analysis, CNNs initiate the processing of biopsy images by laying filters on specific portions of the tissue to derive constituents constituting features like the texture, shape and size. So pooling layers follow to pass activation values to subsequent layers while lowering dimensionality by summarizing activation values in certain areas to make them better, more efficient and more credible models.

CNNs have been employed as a helpful aid to diagnose celiac disease since they are able to identify patterns of features in images of duodenal biopsy. For example, CNNs can successfully identify whether the examined tissue is normal, belongs to patients with CD or other inflammatory bowel diseases. The model is trained with a large number of biopsies images where each biopsy image is labeled and from labeled images the network learns out unique patterns associated with celiac disease. The to-and three dimensionality of the CNN transformed the tomographic presentation

allows preserving relations in both vertical and horizontal planes of the image. These improvements have occurred through the use of this deep learning, making more accurate identification of celiac disease faster [35].

4.2 TRANSFER LEARNING FOR CELIAC DISEASE DETECTION

Transfer Learning is a very important technique is machine learning where one model which has been trained for a specific task is used for a new related task with lesser data. In celiac disease diagnosis from biopsy images, it is possible to fine-tune a model pre-trained on other biopsy images (for instance, intestinal tissues from other patients). This technique is very helpful when there is small data set for training a specific model and can enhance the model precision without requiring heavy data collection exercise [35].

4.3 MULTIPLE INSTANCE LEARNING (MIL) IN CELIAC DISEASE DETECTION

Multiple Instance Learning (MIL) is a type of learning used in machine learning when data are grouped into batches instead of being single groups. In the detection of celiac disease using biopsy images, each image must be considered as a set of small areas and these areas are going to be classified as representing a given state (for instance, celiac disease). MIL is applied for inference of these groups of instances, and may increase diagnostic accuracy even if the image contains different and several tissue areas [35].

4.4 RANDOM FOREST AND ENSEMBLE METHODS FOR CELIAC DISEASE DIAGNOSIS

Random Forests and Ensemble Methods are basically two categories of models used in machine learning where accuracy of models is enhanced through combining different models. During the biopsies image for celiac disease diagnosis we train several Independent models like [Random Forest] and to come with final decision, average is taken. These techniques provide good performance since they eliminate bias in their results and help generalize from the results of various models [37].

5. EVALUATION MEASURES FOR CELIAC DISEASE DIAGNOSIS

The process of assessing the celiac disease diagnosis based on deep learning is usually done by different parameters that consider the quality of the classification of images of biopsies. These metrics compute the prediction of the model against the actual ground truth what makes the assessment to be more objective.

5.1 ACCURACY

Definition: Accuracy consists in the percentage of correct samples with regard to the general quantity of the samples. This metric is practical when the distribution of the samples is roundly split between the classes, it is used to measure the effectiveness of a model in categorizing samples in specific classes such that samples which belong to certain categories such as celiac disease, are grouped together and separately from other related but different categories such as normal tissue samples. Used in the studies “Wei et al.” (2019) [30], a classification accuracy of 95.3% was obtained using the given biopsy images demonstrating the precision of the model to detect celiac disease.

Formula

$$\text{Accuracy} = \frac{\text{Number of correct samples}}{\text{Total number of samples}}$$

5.2 PRECISION

Definition: Precision expresses the proportion of correctly identifi es among all the items classified as positive, it is applied in the case when the cost of type II errors (failing to detect celiac disease) is higher than type I errors (incorrect detection of disease). Kowsari et al., (2019) [31] also reported a precise classification result which reached up to 99.7% for biopsy images.

Formula

$$\text{Precision} = \frac{\text{True Positives}}{\text{Total Predicted Positives}}$$

5.3 RECALL

Definition: True positive recall is the ratio of true positive elements correctly identified to all the actual positive elements; it is used where it is necessary to flag maximum positive cases irrespective of False positives are there. Recall is very important in diagnosing celiac disease through biopsy images because the disease must be detected despite the absence of symptoms.

$$\text{Recall} = \frac{\text{True Positives}}{\text{Total Actual Positives}}$$

Formula

5.4 F1-SCORE

Precision and recall are merged together into one metric in the F1-Score. The accuracy measures the rate of true positives and true negatives in the dataset while, f1-Score display the measure of agreement between precision and recall, useful in imbalanced data sets it reduces false positives and picks on the right balance on disease detection. Applied in the papers "Kowsari et al." (2019) [31], an F1-Score of 99.5% were provided to indicate a high Level of both the memorization and recall performance.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Formula

5.5 AREA UNDER THE RECEIVER OPERATING CHARACTERISTIC CURVE (AUC-ROC)

It is a measure that points out the models capability of classifying between the two classes available. It is used for evaluating model performance irrespective of the model's chosen threshold. AUC-ROC analyzes how well the model ranks the object for the variant threshold, discriminating between the positive class (e.g., celiac disease) and negative class (e.g., normal tissue). Used in the studies "Wei et al." (2019) [30], an AUC-ROC of more than 0.95 were obtained for all classes which indicate the model correctly classify the tissue between celiac disease and normal ones.

Formula: AUC represents the area under the curve that shows the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR).

$$\text{AUC} = \int_0^1 \text{True Positive Rate}(FPR)\, dFPR$$

5.6 MEAN ABSOLUTE ERROR (MAE)

Definition: MAE is the measure of the average of the absolute errors of the scale of the difference between prediction and actuality. MAE is useful in making assessments as to the accuracy of such predictions in classification along with predictive values of regression. It is used where there is need to predict the actual error which is likely to occur between the actual and estimated values.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|x_i - x|$$

Formula

5.7 MEAN SQUARED ERROR (MSE)

Definition: MSE is the metric that combines the measures of the average of squared differences between the values predicted and the observed values. MSE is used for evaluating the correctness of the assessments made for a classification or for regression problems. The model performance is assessed in the studies "Wei et al." [30] and "Kowsari et al." [31] using MSE.

Formula

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

6. ANALYSIS AND DISCUSSION

The diagnosis of the celiac disease has particularly benefited from DL and ML in analysing biopsy and endoscopy images. This paper analyses recent advancements of using computer vision applications in the diagnosis of celiac disease and summarises CNNs, transfer learning and hybrid approaches that weaves in ML and DL aspects. It proves that AI is

applicable with various forms of images such as hematoxylin and eosin (H&E) stained biopsy images, endoscopy images, even Raman spectroscopy data to diagnose the disease.

A significant improvement made toward our model in 2024 was the use of ResNet-18 with transfer learning operating on H&E-stained histological images. This model was accurate over 99% in most classes to support the notion that pre-trained CNN architectures can identify patterns in tissue architecture. Likewise, a comparative study of the year 2023, conducted training on ML and DL model like WKNN, boosted trees, and CNN to identify the images of the duodenal endos copy with the accuracy rate of 98.24%. The results demonstrated high accuracy of the model, but this implies that the exclusive use of image data for training underlines the need to integrate various pathological states to avert misclassification.

Another development is using VGG16 in 2024 for transfer learning and obtaining lower accuracy which is 73% may indicate limited number or variation in the dataset. This is less accurate than a 2021 study that employed steerable pyramid transform (SPT) for feature extraction and used various ML classifiers; the study attested to 88.89% correctness in binary cases and only 72% correctness in multi-class. These outcomes indicate that advanced feature engineering with classical machine learning models is still effective although various CNN models generally outperform them in accuracy when tested on big, diverse data sets.

Another technique that has also come out as a viable diagnostic tool is capsule endoscopy. As of 2022 simple ML algorithms like SVM and random forest having hit a 94.1% accuracy where Capsule Endoscopy videos have been the subject. This demonstrates the promise of video data in improving diagnosis and clarifies determine difficulties for video analysis due to its computational intensity. Furthermore, a recent study using Residual CNN (RCNN) on duodenal biopsy images reported accuracy of 95.3% in celiac disease and 91% in normal biopsies showing the reliability of CNN architectures in analysing histopathological images.

In 2024, extending techniques for Raman spectroscopy contributed to the diagnostic capabilities with hybrid models like deep residual shrinkage networks (DRSN) or multi-channel convolutional neural network (MCNN) with 95% and 90.7% accuracies, correspondingly. This approach also shows the effectiveness of spectral data incorporated with DL techniques as a complementary method to imaging. Conversely, the combination of MIL with CNNs in 2022 yielded a remarkable 94.1% of accuracy and shortening the time for the diagnosis of SB, using whole-slide images of duodenal biopsy, hence making a point that other complex learning paradigms are key in managing large-mass histological data.

In general, the analyzed articles give weightage to the revolutionized use of AI in the diagnosis of celiac disease. Besides histological images, the analysis encompasses video sequences and spectral data to improve diagnostic performance and expand the sphere of automated pathology. Possible future work should include: continuing to increase the number and variety of datasets used including video processing in real time; and using an ensemble model to enhance diagnosis assurance and the scope of areas in which they might be applicable.

The kinds of data employed in diagnosing celiac diseases employing machine learning and deep learning approaches are also different; data utilization enhances diagnostic capability. Among them the Hematoxylin and Eosin (H&E) stained biopsy images which are the most widely used in histopathological examination of intestinal tissue and employed for deep learning training of ResNet-18 and VGG16. Duodenal endoscopy images are also used to provide direct viewpoints on the states of the small intestine, employing algorithms, including WKNN and CNN. Further, images from capsule endoscopy, which is a relatively new method of video capsule endoscopy of the small bowel is diagnosed using methods such as algorithms SVM, random forest. Raman spectroscopy data has also been used for differences samples' spectra, which has improved the diagnosis of the disease by increasing DRSN and MCNN hybrid models' performance. In addition, there are some studies in which the authors have applied more than one instance learning methods, namely MIL methods, to mostly WSI of duodenal biopsies. Meanwhile, the RGB biopsy images have been processed by common machine learning methods, such as SVM and Decision Trees. These data sources help enhance diagnostic efficacy together with complicated the sphere of analysis utilizing AI methodologies. Figure 4 presents a comprehensive comparison of these diagnostic approaches.

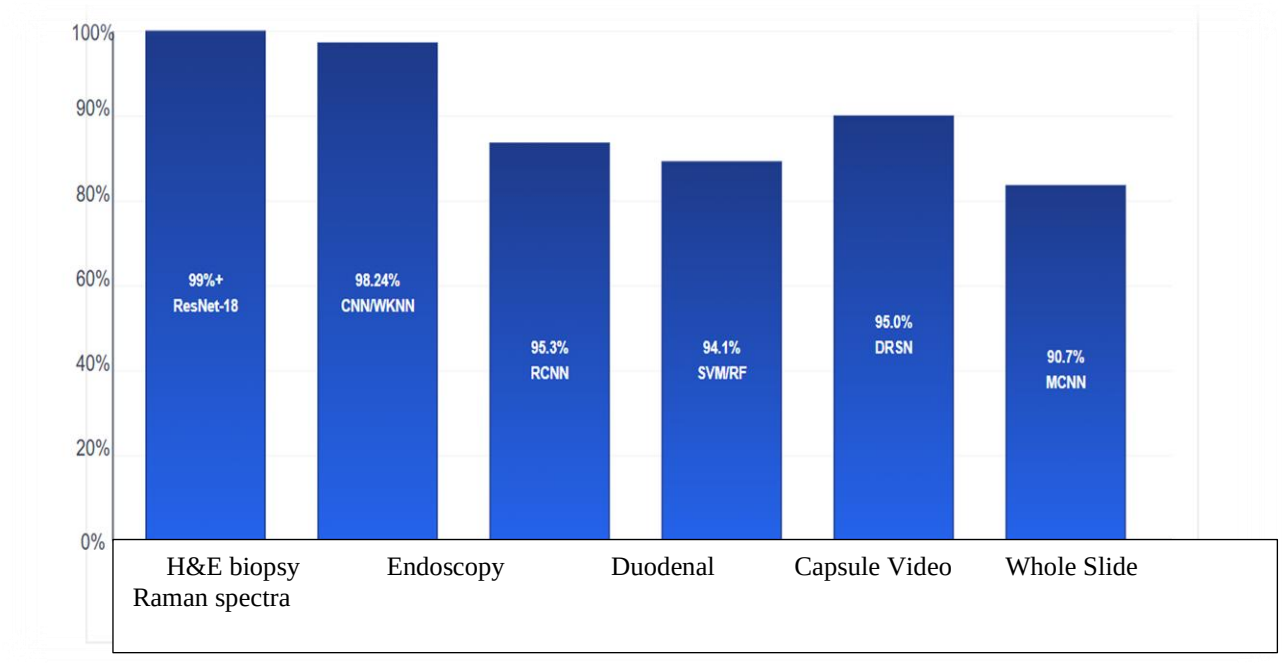

FIGURE 4. - Comparative analysis of AI diagnostic performance across different celiac disease data modalities

The investigation based on celiac disease diagnosis with the help of ML and DL works involve various methodology tools to improve the diagnostic outcomes. Such tools are of different algorithms like Convolutional neural networks (CNN), Residual convolutional neural networks (RCNN), ResNet, and VGG16 for analyzing biopsy image and endoscopic databases. In some of the work, transfer learning is applied by fine-tuning a model on the target domain data for achieving high accuracy despite limited amounts of data. Other works also use feature extraction methods popularized by the Steerable Pyramid Transform (SPT) for image enhancement and classification. Moreover, effort has been made to design models based ML together with DL where SVM's, KNN and Random Forests are used improve the performance of the model on different dataset. In certain papers, authors apply Multiple Instance Learning (MIL) to whole-slide images (WSIs) of biopsies, which appears to be very effective in coping with huge and diverse datasets. These methodologies are integrated with various data types including H&E stained Biopsy Images, Capsule Endoscopy Videos, Raman Spectroscopy Data all of which designed to enhance the accuracy of diagnosing celiac disease. The figure below illustrates the number of research works that applied each of these approaches, highlighting the prevailing trend in this research domain.

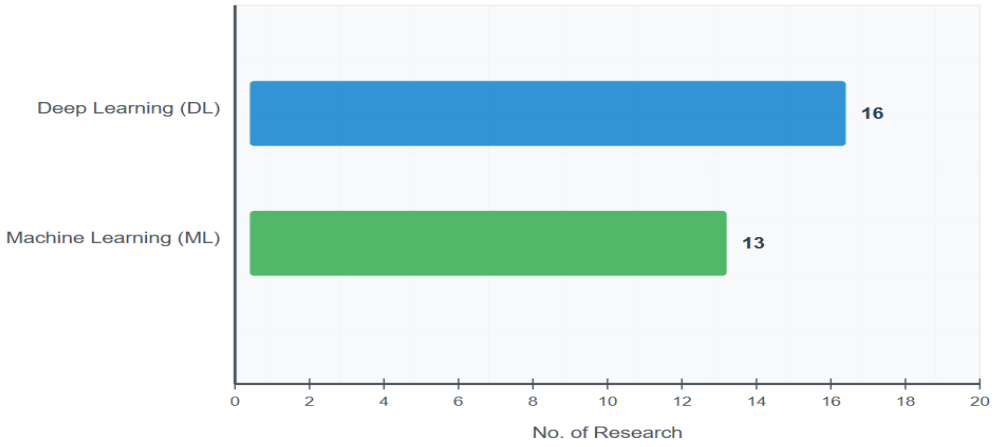

FIGURE 5. - Comparison of the number of studies utilizing Machine Learning (ML) and Deep Learning (DL) techniques in the diagnosis of celiac disease

Various assessment tools have been applied to research about the effectiveness of artificial intelligence in diagnosing celiac disease. They help analyze the success of prediction, the number of errors and how precise and comprehensive the results are. The following figure highlights the main metrics that researchers used in recent studies.

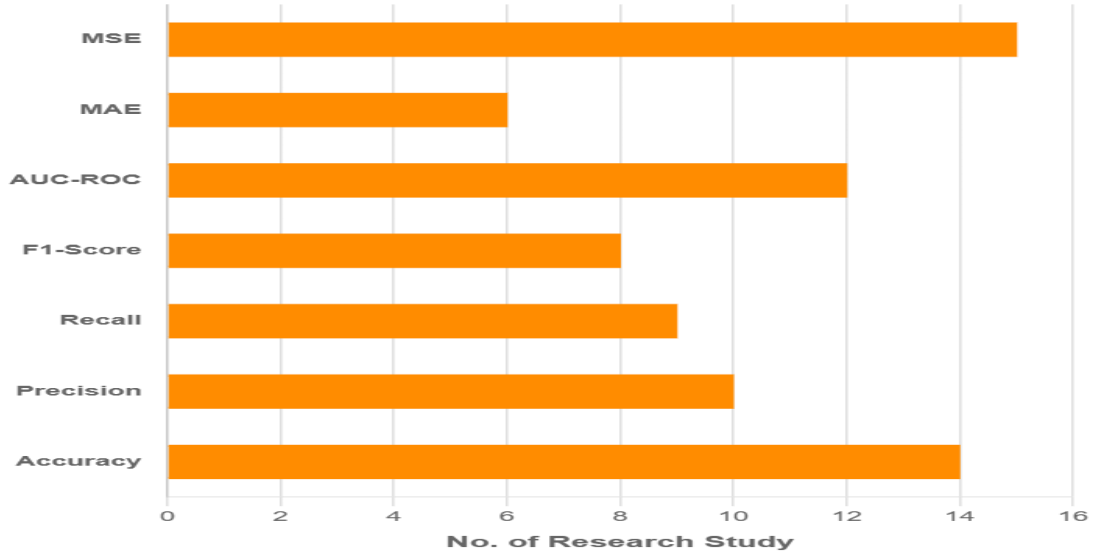

FIGURE 6. - Distribution of evaluation metrics used in previous studies for assessing AI models in celiac disease diagnosis

It includes a review of studies using machine learning and deep learning to diagnose Celiac Disease from biopsy images, endoscopic images or related information. A comparison of these studies has been arranged in a table by considering their publication period, the strategies they use, the algorithms in their methodology, the experiments, types of data involved and the achieved accuracy. A comparative analysis is used to demonstrate the wide range of approaches and to identify gaps the proposed research attempt to fill.

Table 2 Comparison of Previous Studies on Celiac Disease Diagnosis Using Artificial Intelligence Techniques

Ref.num	Year of Publication	Technique used	Algorithm	Method	Data	Accuracy
[28]	2024	Computer Vision	CNN (Convolutional Neural Network)	Transfer Learning (ResNet-18)	Hematoxylin and Eosin (H&E) stained histological images of Celiac Disease, normal small intestine, duodenal inflammation, and duodenal adenocarcinoma	Over 99% for most classes
[38]	2023	Machine Learning (ML) and Deep Learning (DL) Models	WKNN, boosted trees, bagged trees, and (CNN)		duodenal endoscopy images	98.24%

[39]	2024	DL	VGG16, a pre-trained convolutional neural network.	Transfer learning		73% accuracy
[29]	2021	ML	Steerable Pyramid Transform (SPT) for feature extraction combined with various classifiers (Decision Tree, k-Nearest Neighbor, Support Vector Machine, Adaboost, Bagged Trees, Discriminant Subspace).		Hematoxylin and Eosin (H&E) stained biopsy images Red-Green-Blue (RGB) biopsy images	(Two-Class)= 88.89% (Multi-Class)= 72% (Two-Class)= 82.92%
[30]	2019	DL	Residual Convolutional Neural Network (RCNN)		Duodenal Biopsy Images	Celiac Disease)=95.3% (Normal) =91.0% (Nonspecific Duodenitis)=89.2%
[40]	2022	ML	Simple algorithms (e.g., SVM, random forest)		capsule endoscopy. Specifically, the dataset consists of 109 videos	94.1%
[31]	2020	DL	1-Color Balancing. 2-Random Multimodel Deep Learning (RMDL). 3-Shallow Convolutional Neural Network (CNN). 4-Hierarchical Medical Image Classification (HMIC).		duodenal biopsies	
[32]	2022	DL	Convolutional Neural Network (CNN) architectures (specific architectures not explicitly mentioned)	Patch-based approach	Histopathological images of Celiac Disease	Macro-F1 Score: 0.83 Cohen's Kappa (κ): 0.72
[41]	2024	ML With DL	SVM KNN CNN ResNet DRSN MCNN		Raman spectroscopy was used to measure the spectral signatures of these samples.	SVM= 74.28 KNN= 80.23 CNN= 92.31 ResNet=80.2 DRSN=95.0

						MCNN=90.7
[33]	2022	DL	-CNNs -Multiple Instance Learning (MIL)	Multiple-instance learning	Histological WSIs of duodenal biopsies	94.1%
[42]	2024	ML	K-Nearest Neighbor (KNN)- Support Vector Machine (SVM)- Naive Bayes (NB) -Decision Tree (DT)- Random Forest (RF)			80%
[34]	2021	ML	Random Forests, Extremely Randomized Trees, and Boosted Trees, Logistic Regression		Prospective cohort of 340 potential celiac disease children followed up for up to 12 years. * Features include: * Demographics (age, age at biopsy) * Genetics (HLA DQ2 and/or DQ8 positivity) * Serology (anti-transglutaminase IgA and anti-endomysium) * Histology (duodenal biopsies)	All models achieved accuracy above 75%. * Boosted Trees (BT) showed the best performance: * Accuracy: 0.80
[43]	2021	DL	Deep learning convolutional neural networks (CNNs) including one with multizoom architecture		High-resolution biopsy images from 150 children	ResNet50 and shallow CNN demonstrated 98% and 96% case-detection accuracy, respectively, increasing to 98.3% with an ensemble
[44]	2023	ML	Support Vector Machine (SVM)		High magnification biopsy images of duodenal LP from different clinical stages of CD, NCD, and normal Controls	SVM achieved 98.53% accuracy in distinguishing normal controls from CD patients and 98.55% in distinguishing normal controls from NCD
[45]	2023	DL	ResNet18	convolutional neural network	858 endoscopic images from 182 patients with VA (Marsh classification grade III). - 846 images from 323 patients without VA.	84%
[46]	2024	DL	DeepLabV3-RestNet18		H&E-stained duodenal biopsy sections from 349 patients	mean intersection-over-union score of 88.76% and 91.30% was achieved for crypt

						areas and Paneth cell granule segmentations
[47]	2018	ML	• Decision tree (DT) • K-nearest neighbor (KNN) • Probabilistic neural network (PNN) • Support vector machine (SVM)		video capsule endoscopy images	86.47%
[48]	2019	DL	block-wise channel squeeze and excitation (BCSE) with residual network (ResNet) and Inception-v3	block-wise channel squeeze and excitation (BCSE)	video capsule endoscopy images	95.94%
[49]	2021	DL	CNNs	Grad-CAM	**histological images** from duodenal biopsies	88.7%
[50]	2025	ML	Balanced Random Forest	SMOTE-RF	endoscopy images	89.41%
[51]	2019	DL	ResNet50	Transfer Learning	**histological images** from duodenal biopsies	**0.976**
[52]	2024	DL and ML	PyTorch decision tree, random forest, gradient boosting, and naive Bayes		histological examination	**PyTorch Model:** Achieved 80% accuracy in identifying Marsh levels, with precision, recall, and F1-score metrics of 0.81, 0.80, and 0.70, respectively • **Decision Tree, Random Forest, Gradient Boosting:** All three models achieved perfect accuracy of 100%, with precision, recall, and F1-score metrics of 1.00. • **Naive Bayes Classifier:** Performed the worst with 55% accuracy and precision, recall, and F1-score metrics of 0.67, 0.44, and 0.53, respectively.
[53]	2022	DL and ML	C5, logistic regression, Bayesian		Gene Expression Data	95–100%

			network, discriminant analysis, KNN algorithm, LSVM, random trees, SVM, Tree-AS, XGBoost linear, XGBoost tree, CHAID, Quest, C&R tree, random forest, and neural network (multilayer perceptron).			
[54]	2020	DL	Convolutional Neural Networks (CNNs)	Higher Order Spectral (HOS) analysis	endoscopic images	accuracy, sensitivity and specificity ratio are 94.79%, 94.29%, and 95.08%,
[55]	2017	DL	GoogLeNet	Quantitative analysis	Video capsule endoscopy	100٪
[56]	2023	DL and ML	-ANN -Random Forest - SVM-RFE -LASSO	Gene Expression Analysis	Gene Expression Data	
[57]	2019	DL	CNN		duodenal biopsy images	93.4٪
[58]	2016	DL and ML	CNN SVM	Transfer Learning	endoscopic image	90.5%

7. CONCLUSION

Based on the review, CNNs have clear potential to make celiac disease diagnosis more accurate and dependable because of new discoveries in deep learning. Such models can easily detect histological signs linked to a disease and often work better than methods that require a subjective eye examination by pathologists. Some reports found that in combination with ResNet-18, classification accuracy reached well above 99%.

While CNNs are widely used, researchers have also looked into different methods. Researchers can simplify the task of generating big annotated datasets with pre-trained models using transfer learning. Also, Multiple Instance Learning (MIL) stands out by examining parts of images, rather than full slides. With this method, it is easier to study local differences in groups of cells found in histopathological pictures.

Although CNNs excel, the choice of method varies depending on what the data and research involve. For instance, ResNet-18 is usually very effective at classifying histological images, while VGG16 has succeeded in medical imaging in other cases. The best model depends on how complex the data is, how well the model must fit and the resources that are accessible.

Overall, employing deep learning in medical imaging improves the way celiac disease is diagnosed, making the analysis of biopsies speedier and more accurate. Still, further studies are required to solve existing issues such as changes in data, understanding the performance of these models and applying them in hospitals.

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CONFLICTS OF INTEREST

The author declares no conflict of interest.

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