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DIAGNOSIS AND ANALYSIS OF HYPER-TUNING DEEP LEARNING MODEL FOR AUTOMATIC DIAGNOSING CELIAC DISEASE

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Abstract

Celiac disease is an immune system situation that mostly impacts and damages the small intestine as well as the skeletal system. Celiac Disease is prevalent in the modern population. Individuals with Celiac disease are unable to ingest gluten without experiencing negative health consequences. Insufficient awareness often leads to delayed disease identification. Utilizing computer-based prediction could aid in the early identification of Celiac Disease in individuals, increasing their likelihood of maintaining a typical life. The deep learning approach is conducted using hyper-tuning. The hyperparameters of the Mobile Net classifier are optimized using a novel hybrid approach that combines Wheel Plant Optimization and Fruit Fly Optimization. The suggested model is finally assessed and compared with existing approaches regarding Accuracy, Precision, Recall, and Time. The proposed model demonstrated superior performance by attaining an Accuracy of 99.78% compared to the other methods.

Keywords: Celiac disease, Immune system disorder, Hybrid Optimization, Mobile-Net.

I. Introduction

Celiac disease is a problem of the immune system that primarily impacts the small bowel and can lead to systemic consequences. The term "celiac disease" originates with the Greek word "koiliakos," which signifies abdomen [VI]. An allergic reaction to gluten, which is a varied set of proteins that can be found in wheat, barley, and rye1, is the root cause of the disease. The greatest consequences occur in the small intestine, where they create a flammable response that leads to a reduction in villi, resulting in malabsorption, weight loss, and diarrhea. [XXVII]. Patients exposed to these proteins experience an immunological response to impact a variety of tissues, but the most severe effects are seen with small bowel. The small intestine is affected by celiac disease, which is an autoimmune disorder that is initiated by the consumption of gluten in persons who are genetically susceptible to the condition [I]. To effectively manage celiac disease, early identification is required. The disease manifests a wide range of symptoms, which go from gastrointestinal problems to presentations that are not related to the gastrointestinal tract, which makes the identification of the condition difficult. Intervention promptly is necessary to avoid long-term consequences [X]. Despite this, there is a pressing need for more advanced diagnostic techniques. Some of the issues that need to be addressed include symptom heterogeneity, asymptomatic instances, overlap with other illnesses, and limited awareness among the general public and healthcare professionals. There is little doubt that artificial intelligence (AI) has brought about a revolution in the practice of medicine across a variety of professions, including gastroenterology [XI]. Endoscopic operations, ultrasonography images, and histopathological samples in both lumen and hepatobiliary pancreas have already been investigated using computer-aided image processing. Additional research is currently being conducted. There is a wealth of information available in the field of endoscopy on the uses of artificial intelligence for colonoscopy, which is a process that is widely acknowledged to be dependent on the operator [III]. This procedure is also used for Polyp identification and diagnostics as well as bowel cleansing. In this context, AI models have been shown to enhance quality metrics for examinations. Additionally, artificial intelligence has uses in the lower gastrointestinal tract for the treatment of inflammatory bowel disease, including Crohn's disease and ulcerative colitis. These applications are in along with the usage of AI in colon cancer screening programs [XXIV]. Thus, the heterogeneous character of celiac disease symptoms is one of the most significant challenges, as it makes it more difficult to diagnose the condition because individuals show symptoms in a variety of ways. Furthermore, asymptomatic instances present a substantial challenge because individuals may not exhibit any visible symptoms, highlighting the importance of employing diagnostic approaches that are extremely sensitive [XV]. The fact that symptoms of celiac disease coincide with those of other gastrointestinal disorders makes diagnosis even more difficult and requires increased precision to differentiate celiac disease from other comparable ailments [IV, XXII]. In addition, the lack of information regarding the range of symptoms and the incidence of celiac disease is a contributing factor in the delayed diagnosis or incorrect diagnosis of the situation.

Maleki et al. introduced a categorization pipeline in 2021 [XIX]. The pipeline utilized data augmentation, transfer learning, and ensemble learning techniques to train deep convolutional neural networks (CNNs) with a limited dataset. Their pipeline was compared to a standard classification pipeline, and the findings demonstrated that their pipeline displayed higher precision, recall, and accuracy in distinguishing normal tissue CD. The scientists further claimed that their pipeline may be used for a wide range of histopathology imaging applications. Stoleru et al. (2022) [XXVIII] utilized a CNN with two customized filters to detect artefacts associated with CD in endoscopic images. This was achieved by employing a classified machine-learning method that did not include any advanced algorithms. By using capsule endoscopy images, they achieved high accuracy and F1 score, focusing on the non-invasive aspect. The assessment of the efficacy of a gluten-free diet was crucial in terms of clinical importance. In 2019, Wei et al.[XXXI] developed a deep learning model using a cutting-edge residual CNN to assess duodenal tissue patches. They achieved a high level of accuracy in distinguishing between CD, normal tissue, and nonspecific duodenitis. Against verifying the algorithm's efficiency, it references standards provided by pathologists, showing that it yielded consistent findings on a separate dataset. Molder et al. (2023) [XXI] conducted research using duodenal endoscopic pictures of 18 patients with celiac disease (CD) and 16 controls without CD to assess various learning algorithms with automated detection for villous atrophy, an important CD marker. Their research showed that a layered convolutional neural network outperforms other NN models regarding sensitivity, positive predictive value, and diagnostic precision. The authors stated that their method provided a non-invasive way to detect unidentified cases of CD during regular endoscopy, promoting a methodology that eliminated the need for biopsy in diagnosing adult CD.

Calado et al. (2018) [VI] conducted a case-control research investigating the connections between autoimmune disorders (AD) involving 341 adult patients recently diagnosed with CD. Based on the study results, 26.6% of patients with CD experienced at least one AD, with most being related to endocrine and dermatological diseases. Alzheimer's disease (AD) was linked to a positive family history, a body mass index of 25 kg/m2 or above at the time of diagnosis, and a prolonged duration of symptoms before diagnosis. According to the study results, focused CD screening should be conducted on individuals with certain AD-related factors. Sali, et al. (2024) [XXV] used Raman spectroscopy and deep learning algorithms to create a non-invasive, efficient, and highly accurate method for detecting CDs. The collection had a total of 59 plasma samples, comprising 29 patients with CD and 30 healthy controls. The deep residual shrinkage network (DRSN) model demonstrated improved performance by achieving a high level of accuracy and producing impressive area under the curve (AUC) values. The authors emphasized the utility of combining Raman spectroscopy with deep learning for diagnosing CD. Wang et al. (2024) [XXIX] created a revolutionary hybrid architecture that integrates CNN and Transformer. This architecture was specifically created for diagnosing celiac disease based on endoscopic pictures. An advanced spatial adaptive selective kernel convolution with feature attention modules was integrated into the design, proving highly effective in identifying lesions related to celiac disease. The module captured important details in local channel feature maps, focusing on various appearances in regions. Diagnostic capacities were optimized by combining the global representation to converter with location-gathered details using CL. The model's robustness was evidenced by the experiment results, showing high levels of accuracy (98.38%), specificity (99.04%), F1-Score (98.66%), and precision (99.38%).DaFonte et al. (2024) [VII] did a study to understand the role of intestinal permeability in celiac disease autoimmunity (CDA) in at-risk children. An increase in zonulin levels was observed before the development of CDA in the research, which included the analysis of 102 youngsters over a prolonged duration. Zonulin is considered a potential indicator of heightened intestinal permeability, and antibiotic treatments are the sole factor that notably influences the levels of zonulin in persons with CDA. This study's findings offer valuable insights into the temporal dynamics and influencing factors related to intestinal permeability before the onset of CDA. Research gaps in celiac disease studies include limited diversity in data sources, inconsistent diagnostic criteria, delay, and the need for validation in biopsy-avoiding strategies. Integration of data, exploration of early predictors, and addressing real-world implementation challenges are crucial for advancing diagnostic methods and improving patient outcomes. Bridging these gaps can enhance the reliability, applicability, and accessibility of celiac disease diagnostics in diverse clinical settings.

The remaining sections of this work are structured as follows. The second subsection mentions works related. Section 3 evaluates the pre-processing dataset and classification which include the proposed hybrid optimization algorithm. Section 4 discusses the result. Section 6 discussed the conclusion of the paper.

Problem Statement

The incorporation of multiple types of data, such as genetic, clinical, and lifestyle characteristics, into deep learning models facilitates the development of an all-encompassing comprehension of the risk factors associated with celiac disease. Through the examination of a wide range of characteristics, these models can recognize minor patterns that are suggestive of celiac disease. This enables earlier intervention and reduces the difficulties that are associated with the condition. The multifaceted nature of the disease is taken into consideration by this holistic approach, which increases the accuracy of early detection. In addition to technological elements, educational activities concerning the symptoms of celiac disease, the prevalence of the condition, and the significance of early identification might further enhance the impact of hyperspectral deep learning in healthcare settings that are based in the real world.

Contribution

- A hyperparameter tuning-based deep learning system shows potential in aiding the early identification of celiac disease.
- Therefore. A hybrid optimization approach is created by combining the Waterwheel Plant Optimization Algorithm with the Fruit Fly Optimization Algorithm to fine-tune the settings of Mobile Net for feature extraction to aid in the classification of celiac disease.
- Optimizing hyperparameters in deep learning models improves accuracy in diagnosing celiac disease by increasing precision and sensitivity while decreasing false negatives and false positives.

II. Proposed Model

To avoid this, unnecessary colour fluctuations are eliminated by performing colour normalizing as a necessary pre-processing step before any analysis. The dataset is provided as the input of the preprocessing stage to perform the stain normalization [XXVI]. Then, the Mobile Net V2 deep model is employed for extracting the features. This deep features vector is optimized using a hybrid fruit fly Waterwheel optimization algorithm. The best-selected features are finally classified using the FC layer. The proposed diagram is shown in Figure 1.

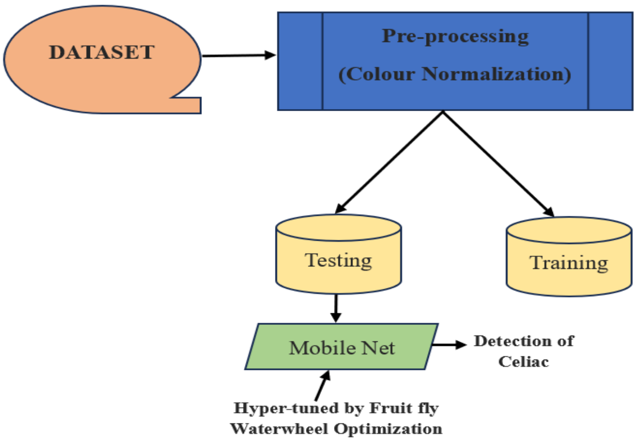

Fig. 1. Proposed Diagram

It provides an updated version of the Mobile Net architecture [XX], a widely used neural network noted for its efficiency and lightweight design, tailored for the specific demands of medical image processing. The selection of MobileNet V2 over alternative architectures is based on its superior trade-off between classification accuracy, computational efficiency, and deployment feasibility in the context of deep learning-based celiac disease diagnosis. Achieving high prediction accuracy in medical image analysis requires taking into consideration hardware limitations, inference speed, and model complexity, especially when developing models for real-time applications or deployment in environments with restricted resources.

Through the use of depthwise separable convolutions, which drastically lower the amount of trainable parameters and computational overhead while maintaining representational capacity, MobileNet V2 has been specially designed for lightweight deep learning applications. This efficiency is especially beneficial in contrast to ResNet, which is less appropriate for real-time diagnostic applications because to its greater computational and memory costs, even with its deeper design and residual connections. In a similar vein, EfficientNet is less feasible for implementation in actual clinical settings, especially on edge devices or cloud-based diagnostic platforms, due to its high memory and computational requirements, even though it is optimally scalable in terms of depth, width, and resolution.

Moreover, MobileNet V2 integrates inverted residuals and linear bottlenecks to enable more efficient feature representation while preserving a small model size. The enhanced generalization and decreased overfitting that these architectural changes bring about are important factors in medical imaging applications where class imbalance and data unpredictability are common.

This framework combines various components to enhance diagnostic accuracy in categorizing medical images and enables the model to be used on devices with limited resources, essential for wider clinical application. Quantization is the act of converting 32-bit floating point numbers into low efficiency. Yet, this mapping may result in quantization mistakes that could impact the precision of the neural network. Scaling factors are utilized to reduce the effects of quantization mistakes. The goal for hyperparameter optimization is to identify the highest achievement metrics [XXI]. That hybrid optimization technique applies an analysis method to identify the most effective hyper-parameters. Begin by determining the hyper-parameters and then specify the values for each hyper-parameter. Below are the specific steps for the algorithm. Thus network weights are converted from floating-point to fixed-point format to lower precision. This entails using a compression algorithm for every weight parameter.

Proposed Fruit fly Water Wheel Plant Optimization

To mimic the water wheel's real behavior, this section begins with setting up WWPA, which explains how to keep the water wheel in one place while it's being explored and exploited. WWPA is a method [XIII] wherein a team member is tasked with solving a particular problem by doing numerous trials inside the designated search area. The dispersed location of the water wheels around the search area caused the WWPA population to return varying findings when tested using various parameters. Each waterwheel stands in for a different vector, which is a graphical representation of many problem methods. The use of such a matrix to depict the entire WWPA population, including all varieties of waterwheels, is not out of the question. The WWPA program begins with a random selection of waterwheel starting locations within the search zone.

$$G = \begin{bmatrix} G_1 \\ \vdots \\ G_a \\ \vdots \\ G_Y \end{bmatrix} = \begin{bmatrix} G_{1,1} & \cdots & G_{1,b} & \cdots & G_{1,x} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ G_{a,1} & \cdots & G_{a,b} & \cdots & G_{a,x} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ G_{Y,1} & \cdots & G_{Y,b} & \cdots & G_{Y,X} \end{bmatrix} \tag{1}$$

$$G_{a,b} = lG_b + r_{a,b}.(\mu G_b - lG_b), a = 1,2, \dots . Y, b = 1,2, \dots , X \tag{2}$$

Where Y and x denote the number of waterwheels and the number of variables, respectively; $r_{a,b}$ is a random value from the interval (0, 1); lG_b and μG_b are the lower and upper bounds of the b-th problem variable, respectively. G is the population matrix of waterwheel sites, G_a is the a-th waterwheel (a candidate solution), and $G_{a,b}$ is the issue variable. Each waterwheel represents a separate approach to the issue, therefore each objective function may be chosen independently. The values that make up the problem's objective function can be effectively expressed as a vector in equation (3).

$$P = \begin{bmatrix} P_1 \\ \vdots \\ P_a \\ \vdots \\ P_Y \end{bmatrix} = \begin{bmatrix} P(M_1) \\ \vdots \\ P(M_a) \\ \vdots \\ P(M_Y) \end{bmatrix} \tag{3}$$

where P is a vector holding all of the objective function values, and P_a represents the anticipated value for the i-th waterwheel. The primary metric for choosing optimal solutions is the evaluation of objective functions. This means that the optimal solution is represented by the goal function with the maximum value. The poorest possible answer is represented by the lowest number, on the other hand. Optimal locations are subject to change over time due to the waterwheels' random exploration of the search region throughout each cycle. At the beginning, we use Eqns. 1 and 2 to randomly distribute the fruit flies around the search space [XVIII].

$$A_m = A\_Axis + RANDOM\ VALUE \tag{4}$$

$$B_m = B\_Axis + RANDOM\ VALUE \tag{5}$$

3 and 4, one may determine the location of each fruit fly and the value of their fragrance strength, respectively. A "RANDOM VALUE" vector is generated at random from a predefined distribution of values. The phase of path construction is performed using Eqns. 3 and 4, one may determine the location of each fruit fly and the value of their fragrance strength, respectively.

$$dist_m = \sqrt{A_m^2 + B_m^2} \tag{6}$$

$$F_m = \frac{1}{dist_m} \tag{7}$$

Where $dist_m$ is the measurement of the radius from i-th participant where the food site, and F_m represents the fragrance saturation assessment level.

• Fitness function calculation phase.
It may be calculated using Equations 5 and 6, accordingly.

$$smell_m = Function(F_m) \tag{8}$$

$$[Best\ smell', Best\ index'] = Max(smell_m) \tag{9}$$

$smell_m$ is the smell concentration of the individual fruit fly, $Best\ smell'$ and $Best\ index'$ indicate the greatest elements and indices along the various dimensions of smell vectors, and $Max(smell_m)$ is the highest smell concentration amongst the fruit flies.

• Movement phase:

The fruit fly retains the highest scent concentration value and will utilize vision to fly to that place using equations 7 and 9.

$$smell\ Best' = Best\ smell' \tag{10}$$

$$A\_Axis = A\ (BEST\ index) \tag{11}$$

$$B\_Axis = B\ (BEST\ index) \tag{12}$$

Algorithm: Hybrid Wheel Plant Optimization (WPO) and Fruitfly Optimization Algorithm (FOA)
Combined Pseudocode for Wheel Plant Optimization (WPO) and Fruitfly Optimization Algorithm (FOA) # Initialize parameters for WPO wpo_population_size = 50 wpo_max_generations = 100 wpo_crossover_rate = 0.8 wpo_mutation_rate = 0.2 # Initialize parameters for FOA foa_population_size = 50

```
foa_max_generations = 100
foa_step_size = 0.1
foa_attraction_coefficient = 1.5
# Initialize problem-specific parameters
problem_dimensions = 10
lower_bound = -5.0
upper_bound = 5.0
# Function to evaluate the objective/cost function
def evaluate_objective(solution):
   # Your objective function implementation here
   pass
# Function for Wheel Plant Optimization (WPO)
def wheel_plant_optimization ()
   # WPO initialization, selection, crossover, and mutation steps
   # Implementation details specific to WPO
# Function for Fruit fly Optimization Algorithm (FOA)
def fruitfly_optimization():
   # FOA initialization, attraction, and movement steps
   # Implementation details specific to FOA
# Combined optimization algorithm
def combined_optimization():
   # Initialize populations for both algorithms
   wpo_population = initialize_wpo_population(wpo_population_size,
problem_dimensions, lower_bound, upper_bound)
   foa_population = initialize_foa_population (foa_population_size,
problem_dimensions, lower_bound, upper_bound)
   for generation in range(wpo_max_generations):
      # Perform WPO iteration
      wheel_plant_optimization ()
      # Select top solutions from WPO for FOA initialization
      top_wpo_solutions = select_top_solutions (wpo_population,
foa_population_size)
      # Replace a portion of the FOA population with top WPO solutions
      foa_population [: len(top_wpo_solutions)] = top_wpo_solutions
      for foa_generation in range(foa_max_generations):
         # Perform FOA iteration
         fruitfly_optimization ()
   # Return the best solution found by the combined optimization
   best_solution = get_best_solution(wpo_population + foa_population)
   return best_solution
# Example of how to use the combined optimization
best_solution = combined_optimization()
print("Best solution:", best_solution)
```

III. Result and Discussion

Dataset and Experiment setup

The University of Virginia (UVa) in Charlottesville, VA, United States, provided the archival biopsies of 34 CD patients, which were used to create 162 H&E-stained duodenal biopsy slides [XXV]. Using the Leica SCN 400 slide scanner (Meyer Instruments, Houston, TX) at the Biorepository and Tissue Research Facility at UVa, 336 full-slide photos were obtained at 40x magnification. This was done because each slide had numerous biopsies per patient. The Python platform is used to examine the dataset [VIII]. Table 1 presents the optimized parameters for the Mobile Net architecture after applying the hybrid optimization approach.

Table 1: Optimized parameter for Mobile Net

Parameters	Optimized Value
Number of Classes	8
Dropout Rate	0.2
Batch Size	32
Learning Rate	0.00005
Max Epoch	50
Optimizer	AdamW
Activation Function	Swish

Hyperparameter tuning plays a critical role in reducing false positives and false negatives, particularly in medical image classification tasks such as diagnosing celiac disease. The optimized parameters presented in Table 1 contribute to enhancing model generalization and minimizing classification errors. For instance, reducing the dropout rate from 0.25 to 0.2 ensures that the model retains more essential features while still preventing overfitting. Similarly, adjusting the batch size to 32 strikes a balance between computational efficiency and model stability, leading to smoother gradient updates. The learning rate, a crucial factor in convergence, has been fine-tuned to 0.00005, ensuring that the model learns effectively without abrupt fluctuations that may lead to misclassifications. Furthermore, increasing the maximum epochs to 50 allows the model to learn deeper feature representations, preventing premature convergence that could result in a high false negative rate. The adoption of the AdamW optimizer enhances weight decay control, reducing overfitting and improving model robustness. Additionally, replacing the traditional Softmax activation with Swish improves gradient flow and enables better feature discrimination, thereby decreasing false positives and negatives. These optimized hyperparameters contribute to refining the MobileNet-based deep learning model, ultimately increasing its reliability and accuracy in automatic celiac disease diagnosis.

Comparison analysis for optimization algorithms

This article presents both the current and new classifiers for human celiac disease, allowing the reader to discriminate between healthy and sick cases. The simulation results demonstrate that the suggested hybrid optimization results in the existing algorithms regarding AF, BF, WF, and SD. These algorithms include GOA-COA [XXIII, XVII], SFO-DHOA [XVIII, XXXV], ROA-AOA [XVI, II], WPA-COA

[XXXI, IX], and HOA-SSO [XX, XIV], which are all versions of the Gazelle and Chimp Optimization Algorithm (GOA-COA). Consequently, the suggested design has shown promise by improving the accuracy of celiac disease classifications. So, the proposed method has been enhanced positively. The results of the investigation using various hybrid optimization algorithms are displayed in Table 2.

Table 2 : Comparison analysis for optimization algorithms

Optimization Algorithm	Average Fitness (AF)	Best Fitness (BF)	Worst Fitness (WF)	Standard Deviation (SD)
GOA-COA	0.21	0.287	0.23	0.083
SFO-DHOA	0.17	0.215	0.19	0.076
ROA-AOA	0.31	0.323	0.28	0.068
WPA-COA	0.11	0.198	0.13	0.054
HOA-SSO	0.03	0.104	0.07	0.096
PROPOSED	0.02	0.008	0.03	0.042

Table 2 shows the statistical assessment of both the suggested, and existing initiatives in this section. Upon analysis, the proposed technique's average fitness value of 0.02 surpasses those of existing approaches such as GOA-COA, SFO-DHOA, ROA-AOA, WPA-COA, and HOA-SSO, which have average fitness values of 0.21, 0.17, 0.31, 0.11, and 0.03 respectively. The graphical representation of the average fitness value in Figure 2 illustrates this.

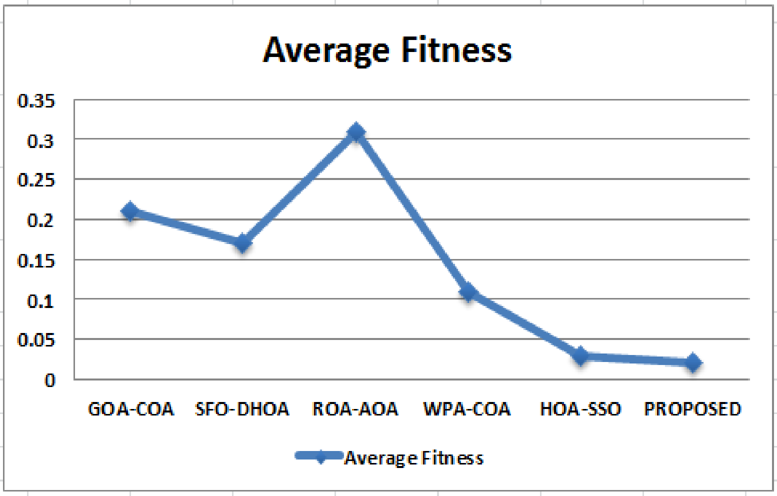

Fig. 2. Average fitness value

Figure 3 displays the best fitness values of the proposed work compared to existing methods: GOA-COA, SFO-DHOA, ROA-AOA, WPA-COA, and HOA-SSO, with values of 0.287, 0.215, 0.323, 0.198, and 0.104 respectively. The proposed approach achieves a fitness value that is 0.008 greater than other existing optimization algorithms as demonstrated in Table 2.

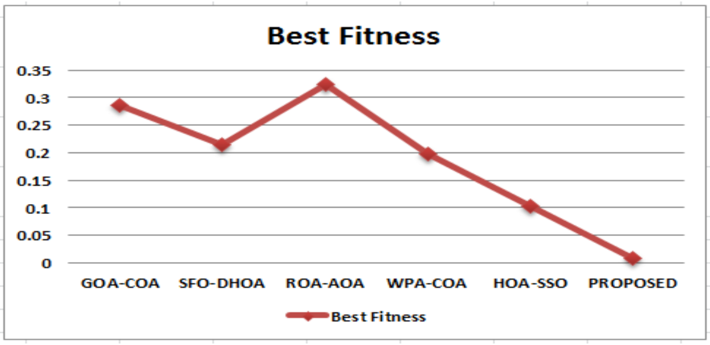

Fig. 3. Best fitness value

A comparison of the worst fitness rates for other optimization algorithms, including GOA-COA, SFO-DHOA, ROA-AOA, WPA-COA, and HOA-SSO, reveals that the worst fitness values for these approaches are 0.23, 0.19, 0.28, 0.13, and 0.07 respectively. This data is presented in Figure 4. The proposed strategy results in other current methodologies concerning performance. The lowest fitness value achieved by a proposed method with an improved fitness rate is 0.03, as displayed in Table 2.

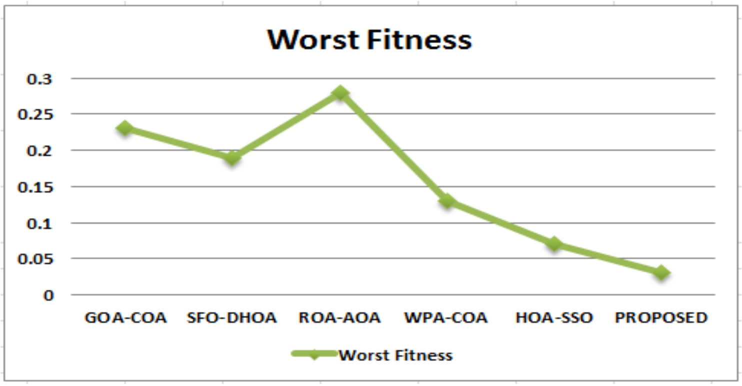

Fig. 4. Worst fitness value

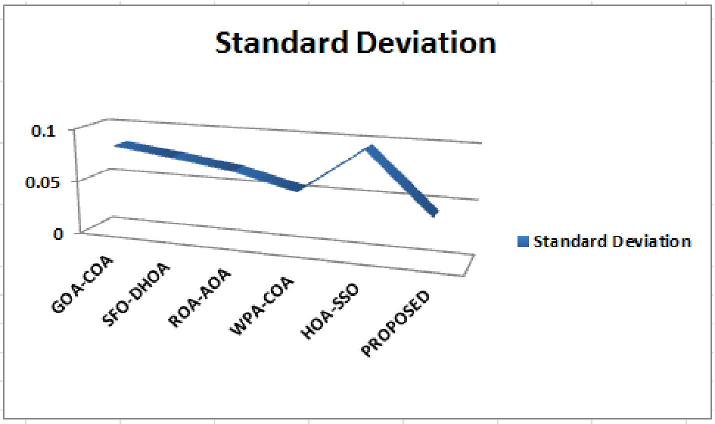

Fig. 5. Standard Deviation value

Table 2 displays the recommended and current methods for measuring STD values. The proposed strategy outperforms previous methods in terms of classification outcomes. The proposed technique has an STD value of 0.042, while other strategies such as GOA-COA, SFO-DHOA, ROA-AOA, WPA-COA, and HOA-SSO have STD rates of 0.083, 0.076, 0.068, 0.054, and 0.096 respectively. Figure 5 illustrates a graphical representation of the standard deviation value.

Analysis of Convergence Computational Time

The time a technology takes to complete a task is called computational time. Table 3 shows the computational time of the suggested and current models. Analyzing the data shows that the proposed classification approach takes 3.1 sec and outperforms GOA-COA, SFO-DHOA, ROA-AOA, WPA-COA, and HOA-SSO by 4.35, 6.48, 4.98, 7.49, and 5.59 sec. The advised strategy worked because running time was lowered. The proposed study is suitable for celiac disease classification. Figure 6 depicts computational time with current methods.

Table 3. Computational time evaluation

Algorithms	Computational Time (sec)
GOA-COA	4.35
SFO-DHOA	6.48
ROA-AOA	4.98
WPA-COA	7.49
HOA-SSO	5.59
PROPOSED	3.16

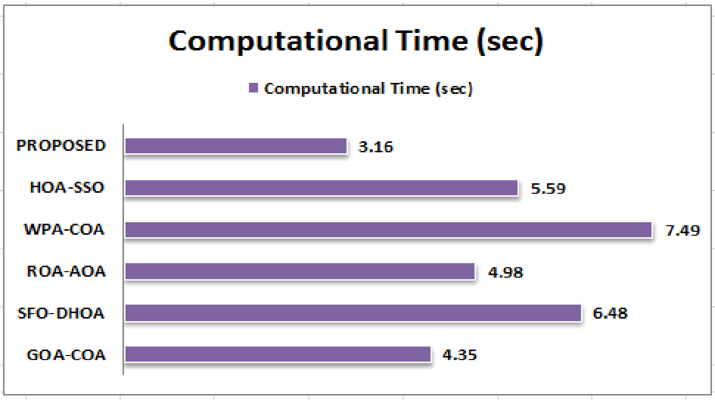

Fig. 6. Computational time analysis

Performance analysis using metrics of the Proposed Model with Existing approaches

The many methods of categorizing are discussed, and a comparative study is carried out to assist in picking the most suitable approach that is suitable for the assignment that is sought. Recall, specificity, sensitivity, F-measure, precision, FNR, FPR, area under the curve (AUC), and accuracy were taken into consideration when evaluating the model. For the technique's efficiency, thus results are compared to those obtained by five different hybrid optimization algorithms that include a classifier. These methods are as follows: GOA-COA+ EcNet, SFO-DHOA+MLP, ROA-AOA+ RNN, WPA-COA+RBF, and HOA-SSO+CNN. The classifier and optimization technique that was suggested achieves a higher performance rate in comparison to other systems that are already in use, suggesting that it is superior to earlier methods for accurately classifying celiac disease. A performance study comparison of the categories that are recommended and those that are already in place is presented in Table 4.

Table 4. Performance study comparison of recommended and existing categories

Performance Metrics	Hybrid Optimization Algorithms					
	GOA-COA+ EcNet	SFO-DHOA+ MLP	ROA-AOA+ RNN	WPA-COA+RBF	HOA-SSO+CNN	PROPOSED
Recall	93.57	91.67	76.04	96.12	92.75	98.89
Precision	85.23	93.67	85.78	95.78	89.75	98.46
Accuracy	94.23	95.97	79.02	96.85	96.21	99.78
F-measure	96.37	94.98	81.00	95.14	91.88	98.74
Sensitivity	89.65	90.54	83.52	91.54	88.84	97.48
Specificity	84.86	89.66	88.41	89.67	87.99	96.83
FPR	47.93	64.98	45.76	51.74	61.65	72.37
FNR	56.83	74.31	69.34	63.97	59.76	77.46
AUC	66.34	71.53	70.04	51.89	72.87	81.95

Figure 7 shows comparisons between the proposed model and five existing hybrid optimization methods with classifiers: GOA-COA+ EcNet, SFO-DHOA+MLP, ROA-AOA+ RNN, WPA-COA+RBF, and HOA-SSO+CNN. The proposed approach has a recall value of 98.89%, while other recommended algorithms have recall values of 93.57%, 91.67%, 76.04%, 96.12%, and 92.75% correspondingly. The suggested design notably outperformed several optimization tactics, achieving a higher recall rate compared to other current approaches.

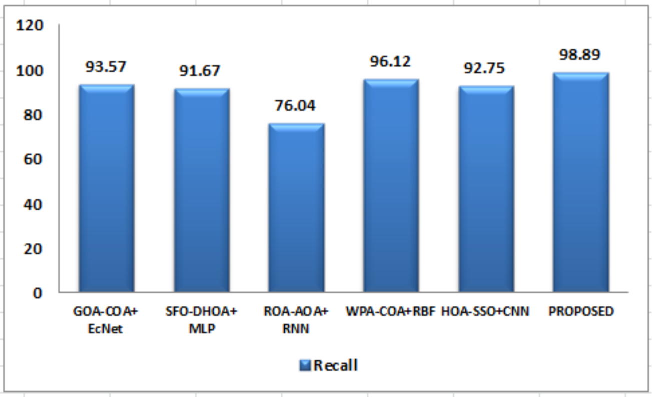

Fig. 7. Performance analysis of Recall with proposed and existing method

Figure 8 displays a graph illustrating the precision findings to demonstrate the usefulness of the proposed approach. The simulation demonstrates that the suggested methodology achieves a precision rate of 98.89%, outperforming existing methods such as GOA-COA+ EcNet (85.23%), SFO-DHOA+MLP (93.67%), ROA-AOA+ RNN (85.78%), WPA-COA+RBF (95.78%), and HOA-SSO+CNN (89.75%).

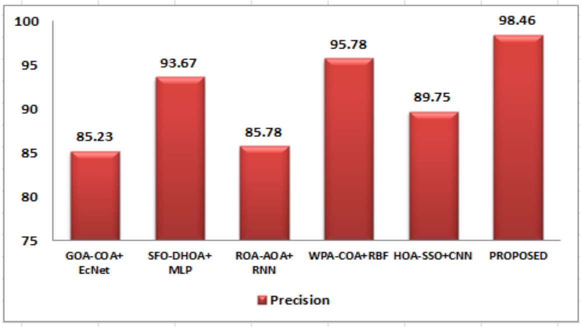

Fig. 8. Performance analysis of Precision with proposed and existing method

The suggested methodology has an accuracy of 99.78%, the highest among all examined methods as shown in Table 4. The suggested strategy achieved the highest accuracy values among all alternatives: 96.85% for WPA-COA+ RBF and 96.21% for HOA-SSO+ CNN. Figure 9 illustrates this graphically.

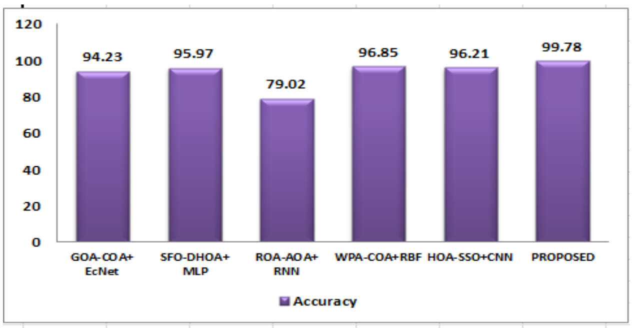

Fig. 9. Performance analysis of Accuracy with proposed and existing method

Figure 10 displays the F-measure of the suggested strategy compared to different existing approaches. The F-score of the suggested algorithm surpasses that of all other known approaches. The proposed approach achieves a success rate of 98.74%. The other available algorithms have sensitivity rates of 96.37%, 94.98%, 81%, 95.14%, and 91.88%.

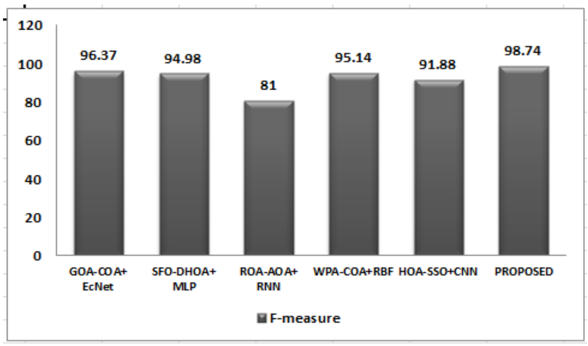

Fig. 10. Performance analysis of F-measure with proposed and existing method

Table 4 displays the sensitivity rates, which are viewed in Figure 11 to evaluate the outcome that was performed suggested method compared to previous techniques. The suggested Model demonstrates better sensitivity compared to other conventional techniques, achieving 97.48%. GOA-COA+ EcNet, SFO-DHOA+MLP, ROA-AOA+ RNN, WPA-COA+RBF, and HOA-SSO+CNN algorithms produce FPR ratios of 89.65%, 90.54%, 83.52%, 91.54%, and 88.84% respectively.

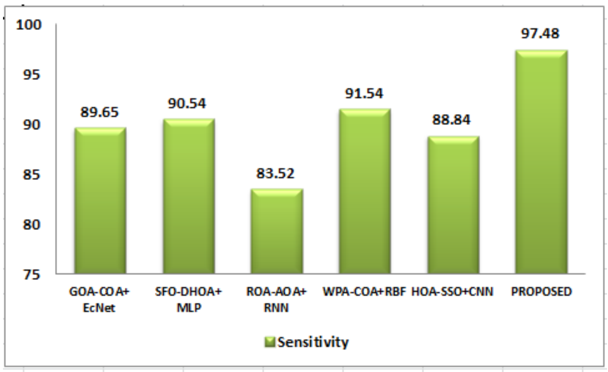

Fig. 11. Performance analysis of Sensitivity with proposed and existing method

Figure 12 examines and compares the specificity of the proposed technique with existing methods. The inquiry outcomes indicate that the recommended approach has a higher specificity value compared to other optimization strategies, such as GOA-COA+ EcNet (84.86%), SFO-DHOA+MLP (89.66%), ROA-AOA+ RNN (88.41%), WPA-COA+RBF (89.67%), and HOA-SSO+CNN (87.99%).

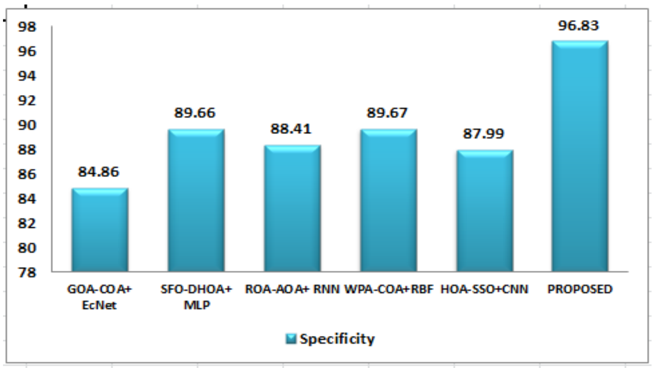

Fig. 12. Performance analysis of Specificity with proposed and existing method

Figure 13 shows that the proposed algorithm analyses the simulation results of False Positive Rate (FPR) at 72.37%. The FPR values are calculated based on various comparative algorithms, such as GOA-COA+ EcNet, SFO-DHOA+MLP, ROA-AOA+ RNN, WPA-COA+RBF, and HOA-SSO+CNN, achieving FPR rates of 47.93%, 64.98%, 45.76%, 51.74%, and 61.65% respectively. The proposed strategy had a greater false positive rate compared to other existing approaches but performed better in classifying celiac disease.

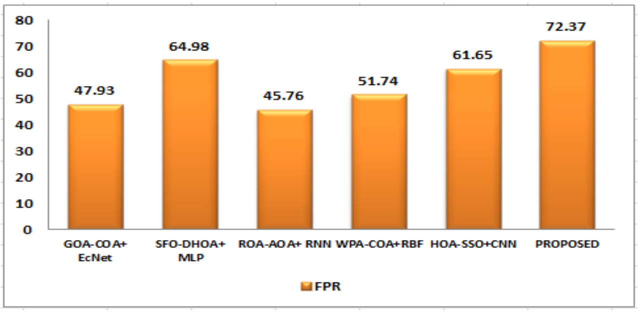

Fig. 13. Performance analysis of FPR with Proposals and current methods

Fig 14 illustrates FNR analysis speed comparing proposed and current approaches. The suggested strategy has a false negative rate (FNR) of 77.46%, while other approaches have FNR rates of 56.83% for GOA-COA+ EcNet, 74.31% for SFO-DHOA+MLP, 69.34% for ROA-AOA+ RNN, 63.97% for WPA-COA+RBF, and 59.76% for HOA-SSO+CNN. The suggested model outperformed other techniques in terms of results.

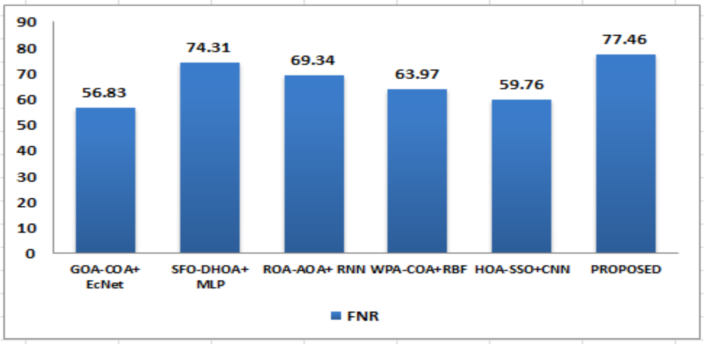

Fig. 14. Performance analysis of FNR with proposed and existing method

The AUC value of the recommended algorithm is 81.95%, surpassing the AUC values of other algorithms such as GOA-COA+ EcNet (66.34%), SFO-DHOA+MLP (71.53%), ROA-AOA+ RNN (70.04%), WPA-COA+RBF (51.89%), and HOA-SSO+CNN (72.87%). The suggested methodology yields the largest AUC quantity compared to the previous methods. Figure 15 displays the AUC analysis comparing suggested and existing techniques.

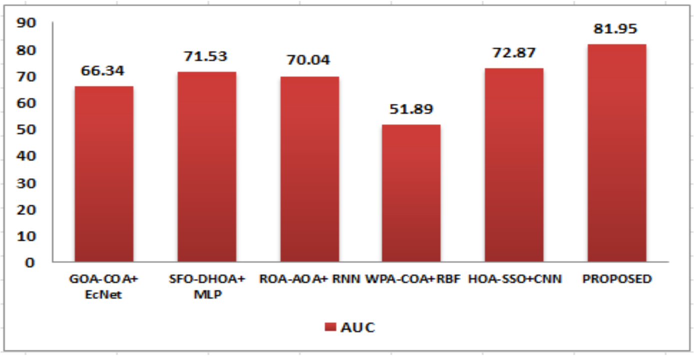

Fig. 15. Performance analysis of AUC with proposed and existing method

Figure 16 displays the comprehensive performance of confusion measures for several approaches including GOA-COA+ EcNet, SFO-DHOA+MLP, ROA-AOA+ RNN, WPA-COA+RBF, and HOA-SSO+CNN. The proposed model outperforms existing strategies in terms of all measures.

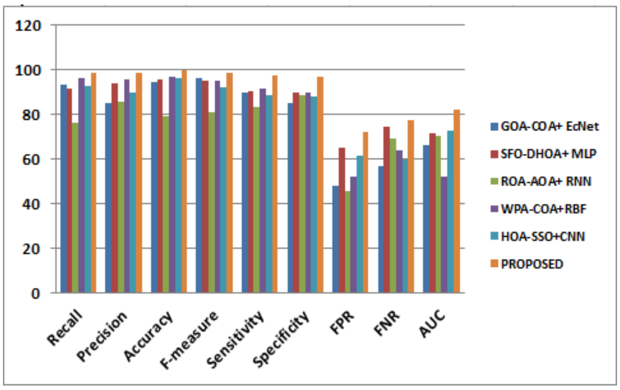

Fig. 16. Overall Performance analysis of the proposed and existing method

According to Table 4, the FPR, FNR, and MCC are shown in Figure 17 to analyze the effectiveness of the suggested approach using current techniques. In this manner, the FPR, FNR, and MCC of the proposed Model are superior compared to other conventional approaches with 72.37%, 77.46%, and 78.95% respectively. The existing algorithms such as (CD-LAMP, OTDEM, PLS-DA, HML-PCD, and SFO-DHA) achieve ratios of FPR is 47.93%, 64.98%, 45.76%, 51.74%, and 61.65% respectively. The ratio of FNR is 56.83, 74.31, 69.34, 63.97 and 59.76 respectively. The ratio of MCC is 66.34, 71.53, 70.04, 51.89 and 72.87 respectively.

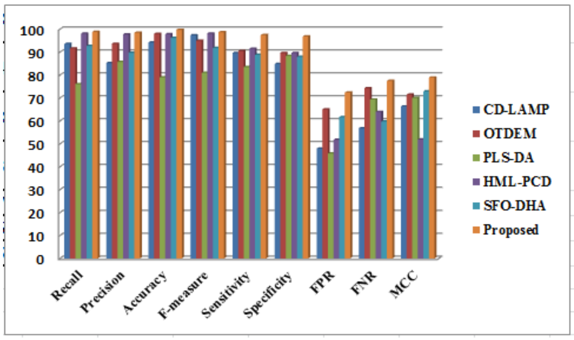

Fig. 17. Overall performance analysis of proposed and existing approaches

IV. Conclusion

It is crucial to discover celiac disease early because people aren't always aware of the condition. Incorporating a computer-based prediction model, particularly one that uses a deep learning method based on hyper-tuning, shows promise. An innovative approach is shown by the use of a mobile Net classifier with hyperparameters that have been fine-tuned using a hybrid optimization strategy that combines Wheel plant Optimization with fruit fly Optimization. The suggested model stands out with exceptional performance metrics, boasting a remarkable accuracy of 99.78%, after undergoing thorough review and comparison with current methods. Patients have a greater chance of leading a normal and healthy life as a result, which highlights the need for proactive measures for early disease diagnosis and the promise of modern computational methods in healthcare. Incorporating these planned upgrades and making use of state-of-the-art data augmentation techniques can strengthen the model by feeding it more synthetic data. Better generalizability and performance across a wide range of patient populations may result from this. A more complete picture of celiac disease can be achieved by combining other types of data, like genetic information and patient histories. Better and more comprehensive prediction models may be possible as a result of this combination.

Conflict of Intrest

There is no conflict of interest regarding this article.

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