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Research Article

Levy Flight Pelican Optimization Algorithm based feature selection for Multi-Class Gastrointestinal Disease

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ABSTRACT

Endoscopic image analysis plays a crucial role in diagnosis Gastrointestinal Diseases (GD) by allowing visualization of the inner tissues of gastrointestinal tract. However, quality of gastrointestinal images is often suboptimal and GD classification are complex and require multiple parameters to training, affecting their accuracy. In this research, proposed Levy Flight Pelican Optimization Algorithm (LFPOA) and Ensemble Machine Learning (ML) method for classification using methods like Multi-Support Vector Machine (MSVM), K-Nearest Neighbour (KNN), Random Forest (RF), Decision Tree (DT) and Naïve Bayes (NB). The LFPOA reduces dimensionality, balances exploration and exploitation, leads to a global optimum, helping to select relevant features. The EL combines five machine learning techniques to handle multiple classifiers and produce a single output, often leading to higher accuracy. Initially, data are obtained from Kvasir V1 dataset and pre-processing is performed using Adaptive Histogram Equalization (AHE) for image quality enhancement. Feature extraction is conducted using MobileNetV2 and InceptionV3, which use separable convolution and layer resizing to efficiently learn from GD images. The performance of proposed method achieved a high accuracy of 99.25% on Kvasir V1 dataset, compared to existing methods such as Stacked Long Short-Term Memory (SLSTM) and Mask Recurrent-Convolutional Neural Network (R-CNN).

Keywords: *Adaptive Histogram Equation, Ensemble Learning, Gastrointestinal Diseases, Levy Flight Pelican Optimization Algorithm and Multi-Support Vector Machine.*

1. INTRODUCTION

Gastrointestinal diseases cause millions in healthcare costs and result in one hundred thousand deaths annually. According to related studies, the cost is considered to be in the billions of dollars each year in the US [1]. Developments in Deep Learning (DL) and Machine Learning (ML) have found applications in various fields of medicine, including, radiology, pathology, dermatology, ophthalmology, and endoscopy [2]. The diagnosis of gastrointestinal diseases is typically made through colonoscopy. However, this method has some drawbacks, including complications like bleeding, infection, pre-examination preparation, and quality indicators [3]. The GD often originate from gastrointestinal polyps, which are abnormal tissue growths on the mucosa of the stomach and colon. These polyps grow slowly, and symptoms typically only appear once they have grown large [4]. Diagnosing polyps involves examining multi-class images in endoscopy. During the exhaustive process of endoscopy, radiologists can fail to detect the polyps [5]. Endoscopy is a minimally invasive procedure that uses a flexible, thin, and elongated tube called an endoscope to visualize patient's internal organs [6]. Due to the high reliance on gastroenterologists for the endoscopic assessment of illness classification, outcomes vary from one expert to another. Manually examining endoscopic data is inefficient, demands essential concentration, and be erroneous depending on the experience level of the diagnostician [7-8].

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The most common approaches implemented for image diagnosis are Machine Learning (ML) and Deep Learning (DL), each offering different benefits and drawbacks. These approaches are considered to improve the diagnosis of Gastrointestinal Disease (GD) using Ensemble Machine Learning (ML) method [9]. The GD diagnosis utilizes the Kvasir v1 dataset, which consists of 8 classes. The images in this dataset are of lower quality, making it challenging to identify the classes. Contrast enhancement is applied to improve image quality during the pre-processing phase [10]. Accordingly, the trained model analyse large GD image datasets and perform feature extraction using pre-trained models by separating the layers to extract features [11]. This is achieved through DL techniques that learn patterns from large amounts of GD images, which are otherwise difficult to diagnose. Feature selection using optimization techniques is then employed to choose the most relevant features, aiding in predicting treatment outcomes, which is essential for patient care [12-13]. Therefore, harnessing both labelled and unlabelled data becomes a more preferable strategy by using ensemble ML method. By incorporating unlabelled data into training process, model's generalization and robustness are enhanced, leading to improved diagnostic capabilities in endoscopy [14-15]. However, quality of GD images is often suboptimal and classification are complex, require multiple parameters to be trained, affecting their accuracy. In this research, proposed Levy Flight Pelican Optimization Algorithm (LFPOA) for feature selection and Ensemble Learning (EL) for classification using methods such as Multi-Support Vector Machine (MSVM), K-Nearest Neighbour (KNN), Random Forest (RF), Decision Tree (DT), and Naïve Bayes (NB). The LFPOA reduces dimensionality, balances exploration and exploitation and leads to a global optimum, helping to select relevant features. Classification using EL combines five machine learning techniques to handle multiple classifiers and produce a single output, often leading to higher accuracy.

The main contribution of the research is discussed below;

- Feature extraction using pre-trained models such as MobileNetV2 and InceptionV3 efficiently learns the features by involving separable Conv, resizing the images. This approach helps in selecting relevant features effectively.
- Feature selection with LFPOA balances exploration and exploitation of the feature space, updating the location of features to select the most relevant ones.
- The proposed LFPOA and Ensemble ML method performs efficiently in GD classification by selecting features and utilizing the highest voting mechanisms, which contributes to achieving high accuracy.

The paper is organized as follows: section 2 provides a literature review that summarizes GD classification. Section 3 introduces proposed method utilized by LFPOS. Section 4 discusses the result and comparative analysis. Section 5 discusses the conclusion.

2. LITERATURE REVIEW

This research conducts studies on GD image classification, providing insights into various techniques along with their advantages and limitations.

Abdulrahman Alruban *et al.* [16] presented an Endoscopic Image Analysis for Gastrointestinal Tract Disease using an inspired algorithm with DL (EIAGTD-NIADL) technique based on Stacked Long Short-Term Memory (SLSTM) techniques. This approach was designed to control the flow of information, helping to mitigate the vanishing gradient issue and allowing efficient learning from longer sequences. However, SLSTM increased the number of parameters due to resource investment and is highly sensitive to initial weights, with poor initialization leading to slow convergence.

Salih Aliyi *et al.* [17] introduced a pre-trained transfer learning method using YOLOv5 with minimal fine-tuning of parameters to assist gastroenterologists and enhance decision-making performance. This method was designed to detect gastrointestinal diseases (GD) and achieves high speed and efficiency, balancing accuracy with inference time. It allows users to select the model that best fits their needs. However, YOLOv5 presents challenges as it was resource-intensive, requiring significant computational power. Additionally, detecting small particles can be complex due to difficulties in learning from GD images.

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Mousa Alhajlah *et al.* [18] developed a GD involved in the DL-based Mask Recurrent-Convolutional Neural Network (R-CNN) and fine-tuned the ResNet-50 network, incorporating Ant Colony Optimization using relevant features. This approach performed pixel-level image classification and mask prediction, further improving the accuracy of segmented images. The optimization technique reduced redundant information impacting classification accuracy. However, the R-CNN model requires substantial resources, and during the inference phase, high-resolution images are not properly classified, and a large batch size further increases parameter demands.

Pallabi Sharma *et al.* [19] presented a diagnosis process involving the unique architecture LPNet for classifying colon polyps from colonoscopy images. LPNet used CNN with pooling to reduce the number of parameters and expand the receptive field. It was designed to have a strong local perceptive ability, particularly effective for tasks where local content is crucial, and reduced the parameters and computation required. However, LPNet struggled to capture the global context and long-range dependencies in the data, limiting its generalization to versatile architectures like CNN techniques.

Hyun-Cheol Park *et al.* [20] introduced a GD classification trained on a total of 8 classes, applying Star-Adversarial Generative Neural Network (Star-GAN) for diagnosis. This method performed image-to-image translation across multiple classes using a single model, reducing the need to train separate models for each class, thereby enhancing efficiency. However, the Star-GAN model is complex due to handling multiple images simultaneously, balancing training across different domains requires tuning, and dealing with high-resolution images poses challenges.

From the overall analysis, the existing techniques are seen to have limitations of quality of gastrointestinal images is often suboptimal and GD classification are complex and require multiple parameters to be trained, affecting their accuracy. In this research, proposed LFPOA for feature selection and EL for classification using methods such as MSVM, KNN, RF, DT, and NB. The LFPOA reduces dimensionality, balances exploration and exploitation and leads to a global optimum, helping to select relevant features. Classification using EL combines 5 machine learning techniques to handle multiple classifiers and produce a single output, often leading to higher accuracy.

3. PROPOSED METHODOLOGY

In this research, proposed LFPOA and Ensemble ML method is applied to GD classification based on the KvasirV1 dataset. Pre-processing using Adaptive Histogram Equalization (AHE) is involved to enhance quality of GD images and handle noise. Feature extraction is performed using MobileNet V2 and Inception V3, extracting features based on separable convolution, considering parameters in different filter sizes of the image. Feature selection using the LFPOA method is performed to avoid falling into local optima, reduce dimensionality, and achieve balanced exploration and exploitation of features. Classification is performed using Ensemble ML method. Figure 1. Block diagram of proposed method.

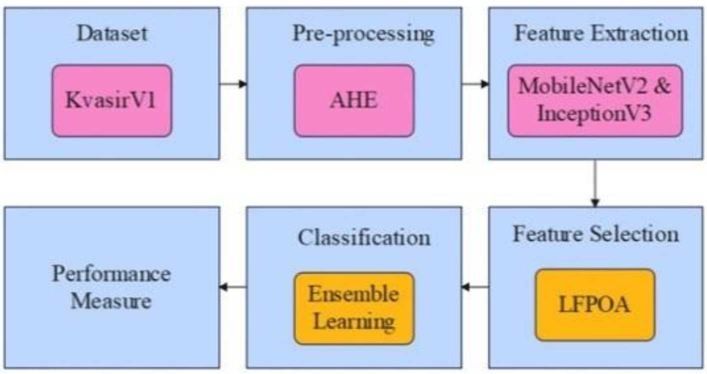

Figure 1: Block diagram of proposed method

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3.1 Data Collection

The KvasirV1 dataset consists of images interpreted by experts, including classes containing endoscopic procedures in the gastrointestinal tract and anatomical landmarks. The dataset contains hundreds of images suitable for use in deep learning and transfer learning. Its pixel resolution of the image ranges from 720 × 576 to 1920 × 1072. After loading the dataset, the image was divided into training 80% and testing 20% sets in the specified ratio. In our work, the dataset contains 8,000 images equally divided into 8 categories: Dyed-Lifted Polyps, Dyed Resection Margins, Esophagitis, Normal Z-Line, Normal Cecum, Normal Pylorus, Polyps, and Ulcerative Colitis. Figure 2. Represent a collected image from the KvasirV1.

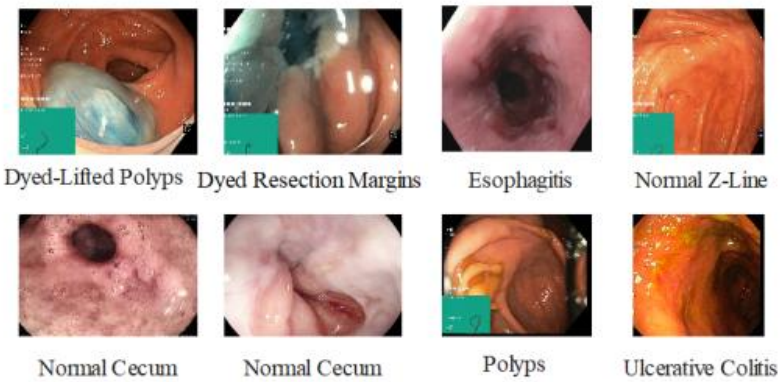

Figure 2: Collected image from the KvasirV1

3.2 Pre-processing

After collecting the data, Adaptive Histogram Equalization (AHE) is involved in the pre-processing step to enhance image contrast, particularly in areas with low contrast affected by GD images. AHE applies different equalization functions to various zone of image based on local image statistics. The image is divided into small regions or tiles, with each tile's histogram being equalized independently. This technique enhances local contrast and improves edge definition in every area of an image. AHE identifies regions of the image where over-amplification occurs and utilizes the HE transmitted function $f(g)$ for gray value g given by AHE is shown equation (1) below:

$$f(g) = \frac{L-1}{n} C(g) = \frac{L-1}{n} \sum_{k=1}^{g} H(k) \qquad (1)$$

Where, n is amount of pixels considered in entire image for classical HE transfers function $f(g)$ given in (1), which is required for evaluating histogram computation. The general computation of $\sum_{k=1}^{g} H(k)$ in worst-case scenario of window contains gray value $g = L-1$ and leads to L additions. To lower computational complexity $C(g)$, utilize solution n within a window is stable, equation (2) and (3) as shown below:

$$n = \sum_{k=0}^{L-1} H(k) = \sum_{k=0}^{g} H(k) + \sum_{k=g+1}^{L-1} H(k)\,, \qquad (2)$$

$$C(g) = \begin{cases} \sum_{k=1}^{g} H(k) & if\, g < \frac{L}{2} \\ n - \sum_{k=g+1}^{L-1} H(k) & otherwise. \end{cases} \qquad (3)$$

Where, summation is split such that most bins need to be added, computation of $f(g)$ requires at most $\frac{L}{2}$ additions or subtractions, as well as multiplication by constant values denoted as $\frac{L-1}{n}$. The AHE computes transfer function of

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each pixel and filters window centered at the pixel. The goal of AHE is to consider local variations in the image, which comes with maximum computational cost. The pre-processed image is then fed into the feature extraction process. Figure 3. Represented the original and pre-processing image.

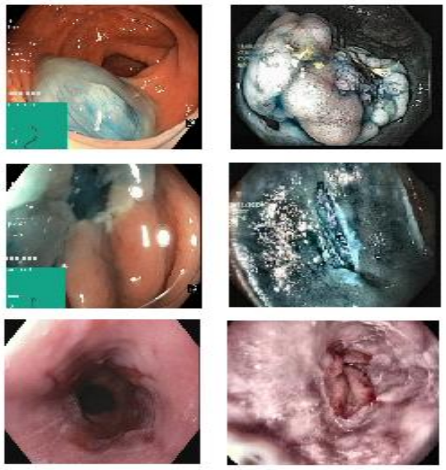

Figure 3: original image and pre-processed image

3.3 Feature Extraction

After pre-processing the data, MobileNetV2 and InceptionV3 are used for feature extraction, utilizing residual and linear bottleneck modules and separated the Conv. It helps to extracted the feature in the GD images. These models are designed to computationally efficient, particularly for mobile and edge devices by using depth wise separable convolution to significantly reduce the amount of parameter. The feature extraction using mobilenetv2 and inceptionv3 achieve high accuracy and combined with different convolutional filters to capture features at multiple scales.

3.3.1 Mobile Net V2

The MobileNet architecture is based on depth wise individual convolutional (Conv), where 2D Conv processes every input channels directly to build 1 outcome channel by Conv in depth dimension. In individual depth wise Conv, stacked outcome channels are then filtered using a 1×1 Conv called pointwise Conv to merge stacked outcomes channels into 1 channel. Depth wise separable Conv produces same outcomes as standard Conv but it is more efficient because its lower number of parameters. MobileNetV2 has 28 Conv layers, resulting in an output size of $7 \times 7 \times 1280$ pixels. The residual block join start and end of a Conv block with a skip-connection to convey data to deeper layers of network. In standard residual block, beginning and end of Conv block usually have more channels than layers in between. This approach ensures better functionality of separable layer, considering depth of gradient descent, which helps achieve maximum classification performance. The network's end block includes a frame with 1×1 Conv layers and a sigmoid activation, enabling network to perform feature extraction effectively.

3.3.2 Inception V3

The InceptionV3 model, widely known as Google Net, is used for feature extraction. It is designed to resize Conv layers and effectively capture both local and global features by using multiple Conv filters of various sizes in parallel. This unique approach alleviates vanishing gradient issue and effective feature extraction at various scales. The model incorporates 1×1 convolutional layers in the initial modules to perceive structure and extract features from input data through Conv operations. It then applies weighting and non-linear transformations to these features using Conv filters and activation functions. The mathematical expressions are shown in equations (4) and (5) below:

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$$x_i = \sum_i y_i w_{ij} + b_i \tag{4}$$

$$f(x) = \begin{cases} 0, x < 0 \\ x, x < 0 \end{cases} \tag{5}$$

Where y_i, w_{ij} and b_i denote input, weight of Conv filter and bias, respectively Conv operation layer involves an activation function to perform a non-linear transformation on output feature. The ReLU activation function is utilized to help alleviate vanishing gradient issue during training and enhance network's learning capability. This allows unique InceptionV3 model to combine parallel Conv filters and efficiently utilize resources, contributing to its effectiveness in handling several gradient descent GD images. The 3×3 convolutional branch captures features, aiding in detecting features such as edges and textures. The 7×7 Conv branch captures larger-scale features, facilitating capture of structure and contextual information. The 3328 extracted features are being fed to feature selection process to reduce dimensionality.

3.4 Feature Selection

After feature extraction, LFPOA method uses feature selection to lower dimensionality of image and select relevant features of GD. The LFPOA is more efficient in exploring search space compared to other traditional methods like particle swarm optimization. It achieves a better balance between exploration and exploitation, leading to maximum convergence and potentially better feature subsets. The high dimensional data is computationally expensive to process and lead to overfitting. So selected feature reduces the number of features making the model more efficient train feature space. The optimized algorithm explores the search space to find the optimal subset of feature and various strategies to balance the recent searching area of the space and refining the current base solution. The selected feature is most efficiently performed help to classification to improving the accuracy. Figure 4. Flowchart of proposed LFPOA method.

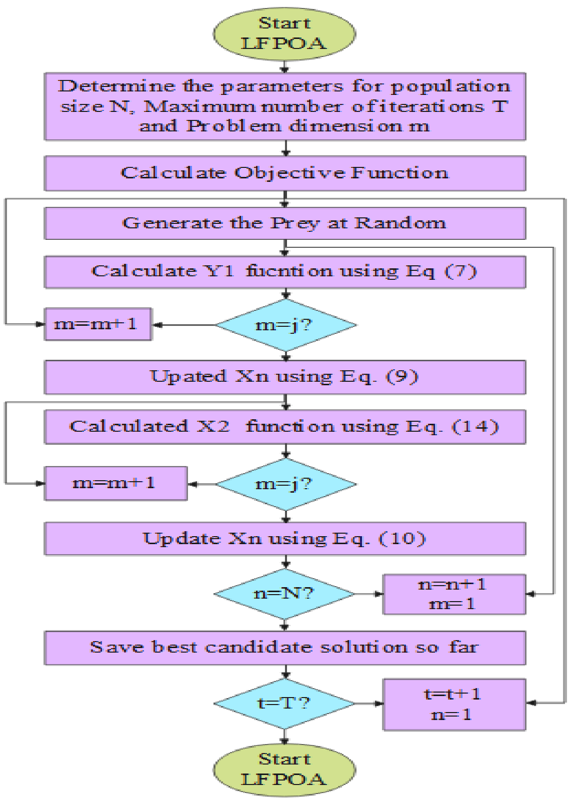

Figure 4: Flowchart of LFPOA method

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The pelican is staying a long time to get the fishes in throat pouch and swallowing prey, serves as an inspiration for the LFPOA method. Pelicans exhibit social behaviour and group coordination. They spread their wings on water's surface to drive fish into shallow areas, making them easier to catch. In optimization process, population members propose values for optimization variables according to their positions in search space. There are 2 main phases in this process: approaching prey phase and surface flight phase.

3.4.1 Moving towards prey

The initial phase of pelican arbitrarily direct velocity of prey and moves toward this fixed on area. This behaviour is mathematically defined to maximum exploration power of POA in discovering different areas of search space. The location of POA is based on prey. The population members are determined arbitrarily according to lower and upper bounds of process, as shown in equation (6) to (8) below:

$$H_n = Y_j, n = 1,2,..,N, j = 1,2,\dots,N \tag{6}$$

$$y_{n,m}^{H1} = \begin{cases} y_{n,m} + rand.\left(H_m - I.y_{n,m}\right), & F_H < F_n \\ y_{n,m} + rand.\left(y_{n,m} - H_m\right), & else, \end{cases} \tag{7}$$

$$Y_n = \begin{cases} y_n^{H1}, & F_n^{H_1} < F_n \\ Y_n, & else, \end{cases} \tag{8}$$

Where H_n denotes prey selected by nth pelican and F_n indicates values of objective function representing degree of adaptation. The j is an arbitrary natural number belonging to interval $[1, N]$. The $y_{n,m}^{H1}$ denotes current state of nth pelican in mth dimension. $F_n^{H_1}$ indicates adaptive value corresponding to new state and rand denotes an arbitrary number in interval $[0, 1]$. These values are updated based on the search space.

3.4.2 Winging on the water surface

The pelican reaches surface and spreads its wings on water, fish are driven to move, allowing pelican to get more fish in targeted area. This behavioural process enables POA to converge rate a best velocity for hunting, which enhances local search and exploitation ability of POA method. The neighbourhood of pelican's location converges to a better solution, and behaviour of pelicans during hunting is mathematically described by the following equation (9) and (10):

$$y_{n,m}^{H2} = y_{n,m} + R.\left(1 - \frac{t}{T}\right).(2.rand - 1).y_{n,m} \tag{9}$$

$$Y_n = \begin{cases} Y_n^{H_2}, & F_n^{H_2} < F_n; \\ Y_n, & else, \end{cases} \tag{10}$$

Where, t indicates new iteration number, T represents maximum number of iterations, and R is a stable value of 0.2. $y_{n,m}^{H2}$ is current phase of nth pelican in mth dimension during second hunting phase, and $y_{n,m}^{H2}$ indicates corresponding fitness values in new state. At initial iteration, value of this coefficient is large, resulting in a broader search area around each member.

3.4.3 Proposed Levy Flight Mechanism with Pelican Optimization Algorithm

Levy flight is effective in POA, enhance its ability to escape local optima and achieve a maximum convergence rate. Levy flights ensure thorough exploration of feature space, while pelican behaviour fine-tunes the search, resulting in high-quality convergence and lower computational overhead. The pelican, combined with Levy flights, explores search space effectively, balancing exploration and exploitation of features. The mathematical expressions are shown in equations (11) to (14).

$$\sigma = [\frac{\Gamma(1+\beta)\sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right)\beta.2^{\frac{\beta-1}{2}}}]^{\frac{1}{\beta}} \tag{11}$$

$$u \sim N(0, \sigma^2), v \sim N(0,1) \tag{12}$$

$$levy(x) = 0.01 \times \frac{u.rand}{|v|^{\frac{1}{\beta}}} \tag{13}$$

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$$y_{n,m}^{H2} = levy.y_{n,m} + R.\left(1-\frac{t}{T}\right).(2.rand-1).y_{n,m} \quad (14)$$

Its expression for 2 stages of POA, after incorporating Levy flight, is shown in (14). This expression updates the global optimum. The proposed LFPOA utilizes a population size in the range of 10-30 and selected feature is 2585 feature. The maximum number of iterations is set between 80.00 to 100.00, and the threshold is considered within the range of 0.10 to 0.50. These parameters are considered in the optimization technique to balance exploration and exploitation, thus enhancing performance.

3.5 Classification

The GD classification uses Ensemble ML method techniques such as Multi-Support Vector Machine (MSVM), Decision Tree (DT), Random Forest (RF), and Naïve Bayes (NB) to independently classify GD. Six techniques are used to train the models individually, with each model learning to select features that frequently contribute to better classification. These methods are combined to predict multiple classifiers and produce a single output, often leading to better performance compared to individual classifiers.

3.5.1 Multi-Support Vector Machine

A multi-class SVM is a generalization of binary SVM. Consider the training set $Z = \{(x_1, y_1), \ldots\ldots, (x_N, y_N)\}$ with N samples, where dimensional eigenvector is K, $x_n \epsilon R^K$, and class label $y_n \in \{1,2,..,M\}$. The training set of data includes M classes. To determine best class, MSVM constructs a binary SVM between each pair of classes. The dashed line d_{12} denotes binary SVM decision boundary between class 1 and 2, and d_{13} denotes decision boundary between class 1 and 3. In this way, all pairs are arranged, and the MSVM is trained to solve the quadratic programming issue, as expressed by equation (15) to (17) shown below:

$$\min_{W^{nm}, b^{nm}, \xi^{nm}} \frac{1}{2}(W^{nm})^T W^{nm} + \sum_t \xi_t^{nm} \quad (15)$$

$$(W^{nm})^T \phi(x_t) b^{nm} \geq 1 - \xi_t^{nm}, y_t = n, \quad (16)$$

$$(W^{nm})^T \phi(x_t) b^{nm} \leq -1 + \xi_t^{nm}, y_t = m, \quad (17)$$

Where W and b are normal vector and offset terms in optimal decision boundary, and ξ denotes an arbitrary number approaching 0, with $\xi \geq 0$. The function ϕ represents nonlinear mapping from input space to feature space, and superscript nm denotes parameter of binary SVM between class n and class m. A total of $C_M^2 = \frac{1}{2}M(M-1)$ binary SVMs are trained for the M class data. The decision function of the binary SVM between classes n and m is expressed by the equation (18) shown below:

$$y_n^{nm} = sign[(W^{nm})^T \phi(x_t) b^{nm}] = sign[\sum y_t a_t^{nm} k(x_t, x_n) + b^{nm}], \quad (18)$$

Where, a is the Lagrange Multiplier and $k(x_t, x_n)$ is kernel function.

3.5.2 Decision Tree

DT are based on ML approaches and are used for both classification and regression analysis. A DT behaves like a hierarchical tree structure with a root node, branches, internal nodes, and leaf nodes. The tree uses properties of information as input to make sequential binary decisions at every node. The input feature values are chosen to less impurities of other variables to greatest extent possible. Information gain is utilized as a metric to establish essential of features in dataset. The GD image is analysed to evaluated a weighted sum for classification, measuring uncertainty of sample values.

3.5.3 Random Forest

The RF algorithm is built using Decision Tree algorithm face certain issues, RF provides a better solution for classification tasks. RF develop various classification and regression trees, every trained on a bootstrap sample of original training data. It searches across an arbitrarily select subset of input variables to determine split. Each tree in RF votes on an input, and output of classifier is determined by majority vote of trees. RF handles high-dimensional data effectively and uses a large number of trees in ensemble ML method.

3.5.4 K-Nearest Neighbour

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KNN is a machine learning algorithm used for both classification and regression purposes. In classification, KNN commonly uses Euclidean distance to calculate distance between data points and determine their neighbours. If distance metric indicates that data points from a particular class are far away, it led to misclassification. To improve classification accuracy, KNN incorporates information about class centres and uses distance formula to classify based on nearest centre point. The classification decision is determined by equation (19) below:

$$d_{min} = \min\{d(t, c_1), d(t, c_2), \ldots., d(t, c_c)\}, \qquad (19)$$

where $d(t, c_1)$ denotes Euclidean distance from test data point t to the centre c_1 of ith class, and $c_1, c_2, c_3, \ldots., c_c$ denote center points of classes. Although KNN handles less separable data by calculating distances, method affected if different class centers are close to each other or equidistant from test point, which impact classification performance.

3.5.5 Naïve Bayes

The NB classifier is a probabilistic model based on Bayes' theorem, resulting in a conditional probability model. It assumes independence of predictor parameters and a Gaussian distribution of metric predictors. NB is designed to evaluated densities using kernel and allows users to specify prior probabilities. When dealing with image data, NB assumes feature independence. The main goal of NB is to evaluated group of GD image by using probabilities of image and categories, including for GD images.

3.5.6 Ensemble Method

Ensemble ML methods enhance predictive performance by integrating various models. In the context of GD, 5 approaches are involved, each based on a different model that generates predictions. These predictions serve as input features for a meta-model. In ensemble framework integrating 5 base models specifically using MSVM, leads to better voting and higher accuracy. Without ensemble ML method, individual models may achieve lower accuracy. The soft voting strategy aims to predict the final result of the GD computing the sum of prediction probabilities of each class among all classify. The mathematically expression by equation (20) shown below;

$$\widehat{X}_i = arg \max_k \sum_{j=1}^{m} w_j P_{i,k}^j \qquad (20)$$

Where, w_j represented the weight of the jth classifier, $P_{i,k}^j$ represent the prediction probability of the jth classifer predicting the sample i into kth class and m is number of classifiers. The ensemble ML method approach efficiently learns and considers frequent values, resulting in a higher voting range and improved performance. Combining individual models that each perform well lead to better overall outcomes.

4. EXPERIMENTAL RESULT

In this research, LFPOA with EL technique is simulated using MATLAB (R2020b), RAM: 16 GB, PROCESSOR: INTEL i5, OPERATING-OS: Windows 10, GPU: 6 GB, SSD: 1TB. The performance measures used for evaluation the feature selection and classification are explained in section 4.1. The performance of proposed method is evaluated using various performance metrics, including Accuracy, Precision, F1-score, Recall and Matthews correlation coefficient (MCC) are defined by equation (20) to (25) as shown below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (21)$$

$$Precision = \frac{TP}{TP + FP} \qquad (22)$$

$$Recall = \frac{TP}{TP + FN} \qquad (23)$$

$$F1 - Score = \frac{2TP}{2TP + FP + FN} \qquad (24)$$

$$MCC = \frac{(TP * TN - FP * FN)}{\sqrt{((TP + FP) * (TP + FN) * (TN + FP) * (TN + FN))}} \qquad (25)$$

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Where, $TP, TN, FP,$ and FN illustrate True Positive, True Negative, False Positive, and False Negatives respectively.

4.1Performance Analysis

In this section, the proposed method involving feature selection and classification processes is evaluated using serval performance metrics, including Accuracy, Precision, F1-score, and Recall, which are presented in Tables 1 to 4. The feature selection and classification process using the KvasirV1 dataset is represented in Tables 2 and 3, which describe the feature selection and classification results. The performance of KvasirV1 dataset feature selection is calculated based on accuracy, precision, F1-score, and recall as described in Table 2. The parameter settings for the LFPOA include a population size of 30 and a maximum of 100 iterations. For PSO, the parameters are set as follows: c1 = 2.00, c2 = 2.00, inertia weight is 1.00, and the population size is 30. These parameters are considered alongside the existing ACO and PSO methods. The existing methods using actual feature selection techniques such as SVM, RF, DE, KNN and NB are evaluated. The Ensemble ML method achieves high accuracy of 99.25%, precision of 99.16%, recall of 99.33%, F1-score of 99.24% and MCC of 98.50% respectively. Table 1. Actual feature of the feature selection.

Table 1: Actual feature of the feature selection

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	MCC (%)
SVM	98.17	98.50	95.87	97.17	92.36
RF	98.27	94.83	90.49	92.61	95.48
DE	98.71	98.33	95.28	96.78	97.10
KNN	97.90	95.67	94.16	94.91	96.78
NB	98.90	96.67	95.38	96.02	97.90
LFPOA and Ensemble ML method	99.25	99.16	99.33	99.24	98.50

The performance of KvasirV1 dataset classification is evaluated based on accuracy, precision, F1-score, recall and MCC as described in Table 2. The existing methods using feature selection techniques such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Dipper Throated Optimization (DTO) and POA are evaluated. The LFPOA method achieves high accuracy of 99.25%, precision of 99.16%, recall of 99.33%, F1-score of 99.24% and MCC of 98.50% respectively.

Table 2: Performance analysis of the feature selection

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	MCC (%)
PSO	91.00	85.27	87.46	85.36	86.26
ACO	90.24	79.36	88.46	84.54	72.36
DTO	93.66	95.37	90.36	92.79	88.37
POA	97.77	98.37	96.49	97.42	97.37
LFPOA and Ensemble ML method	99.25	99.16	99.33	99.24	98.50

The performance of KvasirV1 dataset classification is evaluated based on accuracy, precision, F1-score, recall and MCC as described in Table 3. The existing methods using feature selection techniques such as SVM, RF, DT, KNN

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and NB evaluated. The FFNN with Bi-LSTM method achieves high accuracy of 99.25%, precision of 99.16%, recall of 99.33%, F1-score of 99.24% and MCC of 98.50% respectively.

Table 3: Evaluated the actual feature of Ensemble ML method

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	MCC (%)
SVM	98.17	98.50	95.87	97.17	92.36
RF	98.27	94.83	90.49	92.61	95.48
DE	98.71	98.33	95.28	96.78	97.10
KNN	97.90	95.67	94.16	94.91	96.78
NB	98.90	96.67	95.38	96.02	97.90
Ensemble method	99.25	99.16	99.33	99.24	98.50

Table 4. depict the classification results with different K-fold values of the proposed method using various performance metrics on Kvasir V1 dataset the statistical and time frequency of the ensemble ML method achieves the better outcomes when the K-fold values is 4 compared to the values 3, 7 and 8 respectively. Figure 5 results of confusion matrix, and is a crucial parameter in GD. The confusion matrix analyses classification and measures the accuracy of the proposed method in distinguishing between various classes.

Table 4: Performance analysis LFPOA and ensemble ML method with different K-fold values

K-fold values	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)	MCC (%)
K=3	94.36	95.36	94.26	94.80	91.55
K=5	99.25	99.33	99.16	99.24	98.50
K=7	98.36	97.26	90.33	93.66	91.25
K=8	90.25	97.26	92.25	94.69	95.37

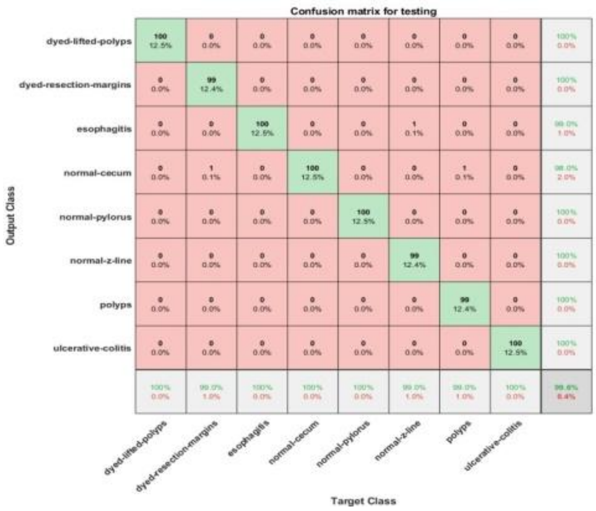

Figure 5: display the confusion matrix of the various classes

4.2 Comparative Analysis

The performance of proposed method LFPOA and Ensemble ML method is compared to existing methods, including SLSTM [16], YOLOV5 [17], RCNN [18], and LPNet-CNN [19]. In this research, proposed LFPOA and

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ensemble ML method achieves high accuracy, reaching 95.25% on KvasirV2 dataset, Table 5. describes a comparative analysis of proposed method. The high accuracy indicates that proposed method effectively classified GD and high precision and recall values reflect its robust ability to identify relevant feature while minimizing false positive and negatives in the GD classification.

Table 5: Comparative analysis of Proposed method on KvasirV1 dataset

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	MCC (%)
SLSTM [16]	98.96	95.85	95.85	95.84	95.25
YOLOV5 [17]	NA	99.07	98.06	NA	NA
RCNN [18]	94.43	NA	NA	NA	NA
LPNet-CNN [19]	93.55	93.55	93.55	93.55	NA
Proposed LFPOA and Ensemble method	99.25	99.16	99.33	99.24	98.50

4.3Discussion

The advantages of the proposed LFPOA and Ensemble ML method are discussed in detail in this section. The LFPOA and Ensemble ML method approach is analysed using the KvasirV1 dataset to evaluate the effectiveness of classifying different gastrointestinal diseases (GD). Initially, image pre-processing is performed using Adaptive Histogram Equalization (AHE) to enhance image quality. Feature extraction is carried out using pre-trained models such as MobileNetV2 and InceptionV3, which utilize separable convolution and resizing to effectively learn from GD images. Feature selection is performed with LFPOA, which uses a hunting process to identify relevant features from the GD images across eight disease classes. LFPOA is compared to other existing methods like Particle Swarm Optimization (PSO) and Differential Tree Optimization (DTO). LFPOA demonstrates superior performance in terms of iteration, exploitation, and exploration of the feature selection space. Classification using Ensemble method, involving five different techniques, achieves higher accuracy compared to other methods. Moreover, LFPOA and Ensemble ML method produces better outcomes than existing approaches such as Stacked Long Short-Term Memory (SLSTM) [16], YOLOv5 [17], R-CNN [18], and LPNet-CNN [19].

5. CONCLUSION

This section, proposed LFPOA for feature selection and EL for classification using methods such as MSVM, KNN, RF, DT, and NB. The LFPOA reduces dimensionality, balances exploration and exploitation and leads to a global optimum, helping to select relevant features. Classification using EL combines five machine learning techniques to handle multiple classifiers and produce a single output, often leading to higher accuracy.[20][21][22][23] Initially, data were obtained from Kvasir V1 dataset, and pre-processing was performed using AHE for image quality enhancement. Feature extraction is conducted using MobileNetV2 and InceptionV3, which use separable convolution and layer resizing to efficiently learn from GD images. The performance of the proposed method achieved a high accuracy of 99.25%, precision of 99.16%, 99.33%, 99.24% and MCC of 98.50% on Kvasir V1 dataset, compared to existing methods such as SLSTM and R-CNN. Future work will consider deep learning techniques for classification to improve accuracy and enhance performance.[24]

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