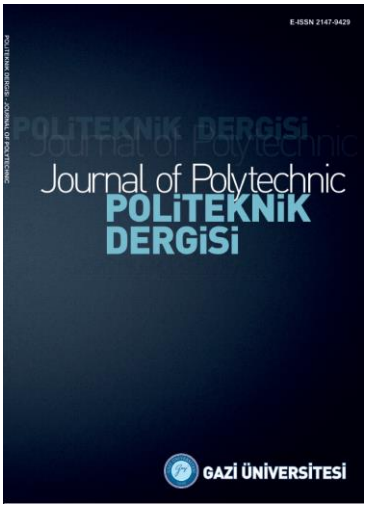

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An approach based on convolutional neural network and ACO-PSO for colon cancer disease diagnosis

Kolon kanseri hastalığının tanısında evrişimsel sinir ağı ve ACO-PSO temelli bir yaklaşım

***Yazar(lar) (Author(s))**: Amna Ali A. Mohamed[1], Raheleh Ghadami[2], Aybaba Hançerlioğullari[3], Javad Rahebi[4]*

ORCID[1]: 0000-0001-8344-6937

ORCID[2]: 0009-0002-9607-4540

ORCID[3]: 0000-0001-7008-480X

ORCID[4]: 0000-0001-9875-4860

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Kolon Kanseri Hastalığının Tanısında Evrişimsel Sinir Ağı ve ACO-PSO Temelli Bir Yaklaşım

An Approach based on Convolutional Neural Network and ACO-PSO for Colon Cancer Disease Diagnosis

Highlights

- *Use CNN methods to extract the features from colon cancer images*
- *Reduce the features numbers with ACO-PSO methds*
- *Use the machine learning methods for classifications*

Graphical abstract

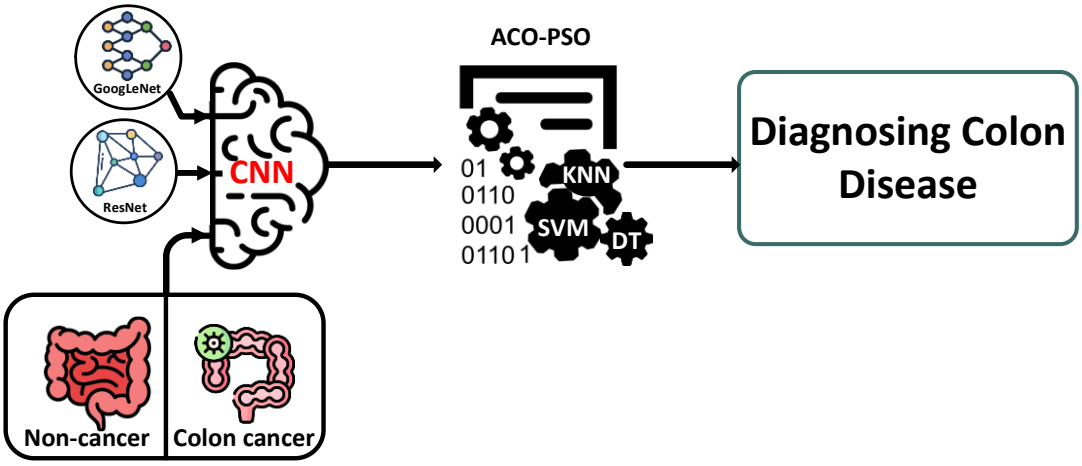

Figure. Graphical abstract for colon cancer disease

Aim

The proposed research aims to address the existing gaps in colon cancer diagnosis methodologies by introducing an innovative approach that leverages the capabilities of CNNs for image analysis and ACO-PSO algorithms for optimizing the model parameters.

Design & Methodology

This article employs two sophisticated methods to enhance the precision of colon cancer diagnosis. It utilizes CNN for extracting features and Ant Colony Optimization-Particle Swarm Optimization (ACO-PSO) for reducing features. These methodologies significantly contribute to refining the accuracy of the colon cancer diagnosis model.

Originality

To identify Cologne illness regions, this article tries to integrate human learning and training with machine learning techniques, like neural network learning.

Findings

results were obtained in the evaluation of metrics, including sensitivity, specificity, accuracy, and F1 score, which were found to be 99.50%, 99.93%, 99.97%, and 99.97%, respectively.

Conclusion

The ACO-PSO algorithm in the suggested method initially improves the precision of the ACO-PSO technique for choosing the specified characteristic by the optimization teaching and learning process.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

An Approach based on Convolutional Neural Network and ACO-PSO for Colon Cancer Disease Diagnosis

Research Article

Amna Ali A. Mohamed[1], Raheleh Ghadami[2], Aybaba Hançerlioğullari[3], Javad Rahebi[4]

[1]Department of Material Science and Engineering, University of Kastamonu, Kastamonu, Turkey
[2]Department of Computer Engineering, Istanbul Topkapi University, Istanbul, Turkey
[3]Department of Physics, University of Kastamonu, Kastamonu, Turkey
[4]Department of Software Engineering, Istanbul Topkapi University, Istanbul, Turkey

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ABSTRACT

The diagnosis of colon cancer has evolved into a global preoccupation, reflecting its profound impact on public health and healthcare systems worldwide. In this study, the diagnosis of colon cancer is performed using convolutional neural networks (CNN) and metaheuristic methods. Various CNN architectures, including GoogLeNet and ResNet-50, were employed to extract features related to colon disease. However, inaccuracies were introduced in both feature extraction and data classification due to the abundance of features. To address this issue, feature reduction techniques were implemented using combined Ant Colony Optimization (ACO) and particle swarm optimization (PSO). Superior convergence speed in optimizing the fitness function was observed in the case of ACO-PSO. With ResNet-50 producing 2048 features and GoogLeNet generating 1024 features, the reduction of feature dimensions proved to be crucial in identifying the most informative elements. Encouraging results were obtained in the evaluation of metrics, including sensitivity, specificity, accuracy, and F1 score, which were found to be 99.50%, 99.93%, 99.97%, and 99.97%, respectively.

Keywords: Convolutional Neural Network, Metaheuristic Methods, Ant Colony Optimization, Colon Cancer

Kolon Kanseri Hastalığının Tanısında Evrişimsel Sinir Ağı ve ACO-PSO Temelli Bir Yaklaşım

ÖZ

Kolon kanseri tanısı, dünya çapında halk sağlığı ve sağlık sistemleri üzerindeki derin etkisini yansıtan, küresel bir endişeye dönüşmüştür. Bu çalışmada kolon kanseri tanısı evrişimsel sinir ağları (CNN) ve metasezgisel yöntemler kullanılarak gerçekleştirilmektedir. Kolon hastalığıyla ilgili özellikleri çıkarmak için GoogLeNet ve ResNet-50 dahil olmak üzere çeşitli CNN mimarileri kullanıldı. Ancak özniteliklerin çokluğu nedeniyle hem öznitelik çıkarımı hem de veri sınıflandırmasında yanlışlıklar ortaya çıkmıştır. Bu sorunu çözmek için, birleşik Karınca Kolonisi Optimizasyonu (ACO) ve parçacık sürüsü optimizasyonu (PSO) kullanılarak özellik azaltma teknikleri uygulandı. ACO-PSO durumunda uygunluk fonksiyonunun optimize edilmesinde üstün yakınsama hızı gözlemlendi. ResNet-50'nin 2048 özellik üretmesi ve GoogLeNet'in 1024 özellik üretmesi ile özellik boyutlarının azaltılmasının, en bilgilendirici öğelerin belirlenmesinde hayati önem taşıdığı kanıtlandı. Duyarlılık, özgüllük, doğruluk ve F1 puanı gibi metriklerin değerlendirilmesinde sırasıyla %99,50, %99,93, %99,97 ve %99,97 olarak tespit edilen cesaretlendirici sonuçlar elde edildi.

Anahtar Kelimeler: Evrişimsel Sinir Ağı, Metasezgisel Yöntemler, Karınca Kolonisi Optimizasyonu, Kolon Kanseri.

1. INTRODUCTION

Colon cancer, a malignant neoplasm arising from the large intestine's inner lining, represents a significant global health concern. Its prevalence and mortality rates underscore the critical need for effective and timely diagnostic methods. Early detection remains pivotal in improving patient outcomes and reducing the overall burden of the disease. With advancements in medical imaging, computational techniques, and data analytics, there is a growing opportunity to enhance the precision and efficiency of colon cancer diagnosis. This research focuses on reviewing the current landscape of colon cancer diagnostic approaches and exploring potential advancements that could lead to more accurate and accessible diagnostic methodologies [1][2].

Historically, colon cancer diagnosis heavily relied on traditional methods such as colonoscopy, biopsy, and

* *Corresponding Author*
e-mail : melisarahebi@topkapi.edu.tr

fecal occult blood tests. While these techniques are effective, they come with challenges such as invasiveness, patient discomfort, and cost. The pursuit of non-invasive and technologically advanced diagnostic tools has driven research toward innovative approaches that leverage the capabilities of medical imaging and computational analysis [3][4].

Radiological imaging modalities, including computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET), have played a crucial role in detecting and characterizing colorectal lesions. These imaging techniques provide detailed anatomical information but may lack the sensitivity required for early-stage detection. Recent developments in imaging technology and contrast agents aim to address these limitations, emphasizing the need for continued exploration and integration with other diagnostic methodologies [5][6][7].

The integration of artificial intelligence, particularly machine learning and deep learning, has shown great promise in improving the accuracy and efficiency of colon cancer diagnosis. Automated image analysis, pattern recognition, and predictive modeling using AI algorithms contribute to early lesion detection and classification. Convolutional Neural Networks (CNNs) and support vector machines (SVMs) have demonstrated notable success in differentiating between benign and malignant lesions, paving the way for their potential integration into routine clinical practice [8][9][10].

Advancements in molecular biology have identified specific biomarkers associated with colon cancer, providing insights into its molecular pathogenesis. Techniques such as DNA testing, gene expression profiling, and detection of circulating tumor markers offer a complementary approach to imaging-based diagnostics. Integrating molecular information with imaging findings holds promise for personalized and targeted therapeutic strategies [11][12].

While significant progress has been made in colon cancer diagnostics, challenges persist, including the need for improved sensitivity in early detection, cost-effectiveness, and widespread accessibility. Future research should focus on synergistic approaches, combining imaging modalities, AI algorithms, and molecular diagnostics to create comprehensive and accurate diagnostic tools. By addressing these gaps, we can enhance the early detection and management of colon cancer, ultimately improving patient outcomes and reducing the global burden of this disease [13].

Colon cancer is a prevalent and potentially lethal disease worldwide, with a substantial impact on public health. Early detection and accurate diagnosis are crucial for effective treatment and improved patient outcomes. In recent years, the integration of advanced computational techniques with medical diagnostics has shown promising results in enhancing the accuracy and efficiency of disease diagnosis. In this context, the fusion of Convolutional Neural Networks (CNNs) and Ant Colony Optimization-Particle Swarm Optimization (ACO-PSO) algorithms presents a novel and powerful approach for the diagnosis of colon cancer [14][15][16].

Historically, colon cancer diagnosis has heavily relied on invasive procedures such as colonoscopy and biopsy. While these methods remain crucial for definitive diagnosis, their invasiveness, cost, and potential discomfort for patients have led researchers to explore alternative, non-invasive diagnostic approaches. The emergence of computational techniques has provided a new avenue for developing accurate and efficient diagnostic tools [17][18].

CNNs have gained remarkable success in various image-based tasks, including medical image analysis. Their ability to automatically learn hierarchical features from complex images makes them well-suited for detecting patterns and abnormalities in medical images. In the context of colon cancer, CNNs have demonstrated impressive performance in image classification and segmentation tasks, paving the way for their integration into diagnostic frameworks [19][20].

The optimization algorithms, ACO and PSO, have shown effectiveness in solving complex problems. Integrating these algorithms with CNNs for medical image analysis introduces the potential for improved feature extraction and model optimization. ACO-PSO hybridization leverages the strengths of both algorithms, providing robustness and efficiency in optimizing the CNN parameters for enhanced diagnostic accuracy [21][22].

Several studies have explored the integration of machine learning techniques with medical imaging for cancer diagnosis. The combination of CNNs with optimization algorithms has been successfully applied in various medical domains, including breast cancer, lung cancer, and melanoma [23]. However, limited research has focused specifically on colon cancer diagnosis using the synergistic power of CNNs and ACO-PSO algorithms.

The proposed research aims to address the existing gaps in colon cancer diagnosis methodologies by introducing an innovative approach that leverages the capabilities of CNNs for image analysis and ACO-PSO algorithms for optimizing the model parameters [13][24]. By combining these technologies, we anticipate achieving a more accurate and efficient colon cancer diagnosis, ultimately contributing to early detection and improved patient outcomes.

In the subsequent sections of the research, we will delve into the methodology, experimentation, and results, aiming to validate the effectiveness of the proposed approach in the context of colon cancer diagnosis [25][26][27].

This paper proposes a new method for colon histopathological image classification that does not need to select features or use principal component analysis (PCA). This article proposes an intelligent feature selection method that uses major features to enhance the precision of colon cancer diagnosis. Table 1 functions as an essential reference guide, serving to abbreviate key concepts and aid readers in grasping the core ideas delineated within the paper.

The proposed approach employs pre-trained CNN models, specifically GoogLeNet and ResNet, to extract features from both colon cancer and non-cancer images. Subsequently, a binary version of the ACO-PSO algorithm is utilized to select optimal features from the extracted attribute data. This integrated approach, utilizing the ACO-PSO algorithm for feature selection and the K-nearest neighbor (KNN) algorithm for classification, has led to the accurate classification of colon disease images. While traditional image processing techniques are used for diagnosing colon disease, they require substantial training for accurate interpretation. This paper aims to classify colon disease by employing a combination of machine learning techniques such as SVM, decision tree (DT), KNN, and ensemble methods. Notably, the proposed method employs the ACO-PSO algorithm to select the most relevant features from pre-trained CNNs like GoogLeNet and ResNet-50, guided by an autoencoder framework.

2. MATERIAL and METHOD

This article employs two sophisticated methods to enhance the precision of colon cancer diagnosis. It utilizes CNN for extracting features and Ant Colony Optimization-Particle Swarm Optimization (ACO-PSO) for reducing features. These methodologies significantly contribute to refining the accuracy of the colon cancer diagnosis model.

In this diagnostic model, CNN are initially employed to extract crucial features from images of colon tissue. These deep neural networks possess the capability to discern intricate patterns within complex medical images, facilitating the identification of anomalies.

Furthermore, to streamline the feature set and eliminate redundant or unnecessary elements, the ACO-PSO technique is utilized. By leveraging collective intelligence inspired by ant behavior and the particle swarm algorithm, this combined approach efficiently selects essential features from the high-dimensional feature space.

The integration of these two methodologies forms a potent combination that markedly enhances the accuracy of colon cancer detection. By automatically identifying pertinent features from images and reducing feature space dimensions, these measures significantly bolster disease diagnosis accuracy, yielding superior outcomes in colon cancer detection.

2.1. Convolutional Neural Networks (CNNs) for Feature Extraction

CNNs were utilized to automatically extract pertinent features from histopathological images depicting both colon cancer and non-cancerous tissues. Specifically, architectures such as GoogLeNet and ResNet-50 were employed for this task. CNNs demonstrate proficiency in learning hierarchical features from intricate images, rendering them well-suited for identifying patterns and irregularities in medical images, including those portraying colon tissues. By employing pre-trained CNN models, the research sidestepped the necessity for manual feature selection or principal component analysis (PCA), processes that can be time-intensive and might overlook certain relevant features. The features extracted via CNNs offered comprehensive representations of the input images, encompassing both subtle and prominent visual cues indicative of colon disease. Table 2 presents a comparison between Principal Component Analysis (PCA) and Ant Colony Optimization-Particle Swarm Optimization (ACO-PSO) methods in reducing specificity for colon cancer diagnosis.

Overall, ACO-PSO demonstrates advantages over PCA in terms of interpretability, handling nonlinear relationships, supervision, discriminative feature selection, adaptive optimization, integration of domain knowledge, and suitability for colon cancer diagnosis.

2.2. Ant Colony Optimization-Particle Swarm Optimization (ACO-PSO) for Feature Reduction:

The profusion of features extracted by CNNs can introduce challenges such as overfitting and heightened computational complexity. Consequently, employing feature reduction techniques becomes imperative to tackle these issues. To address this, the ACO-PSO hybrid algorithm was utilized to pinpoint the most informative features from the high-dimensional feature space generated by CNNs. The ACO-PSO algorithm harnesses collective intelligence inspired by ant foraging behavior

Table 2: Comparison of PCA and ACO-PSO for feature reduction in colon cancer diagnosis

Feature	PCA	ACO-PSO
Interpretability	Lower: Principal components may not directly relate to biological characteristics	Higher: Selected features can be analyzed for biological relevance
Underlying Assumption	Linear relationships between features	Can capture non-linear relationships
Supervised vs. Unsupervised	Unsupervised: Doesn't consider class labels	Supervised: Can incorporate class labels for targeted selection
Feature Selection	Select features based on variance	Selects discriminative features for classification
Optimization	Limited	Adaptive: Iteratively searches for optimal subsets
Nonlinear Feature Selection	No	Yes
Domain Knowledge Integration	No	Can prioritize features based on biological relevance
Overall Suitability for Colon Cancer Diagnosis	May not be ideal for complex data	Well-suited for identifying discriminative features

and the swarm behavior observed in bird migrations to efficiently explore optimal feature subsets. Through iterative refinement of the feature subset using ACO-PSO, the model effectively identifies discriminative features associated with colon disease while discarding irrelevant or redundant ones. Feature reduction proves instrumental in mitigating the curse of dimensionality, thereby enhancing model generalization and improving computational efficiency during both training and inference phases.

2.3. Integration of Techniques:

The combination of CNNs for feature extraction and ACO-PSO for feature reduction constituted a synergistic approach in the realm of colon cancer diagnosis. CNNs served as an Effective instrument for discerning intricate patterns from raw image data, whereas ACO-PSO optimized the feature space to concentrate on the most informative attributes.

This integration yielded a model in precisely categorizing histopathological images of colon tissues, resulting in elevated accuracy rates across diagnosis metrics such as sensitivity, specificity, accuracy, and F1 score.

In essence, the utilization of CNNs for feature extraction coupled with ACO-PSO for feature reduction complemented each other, culminating in a precise and streamlined model for colon cancer diagnosis. This methodology facilitated the automated identification of pertinent image features while addressing challenges associated with high-dimensional data, ultimately contributing to enhanced diagnostic accuracy and favorable patient outcomes. Table 3 illustrates the amalgamation of methodologies for detecting colon cancer.

Table 3: Integration of techniques for colon cancer diagnosis

Technique	Integration
CNNs	Feature Extraction
ACO-PSO	Feature Reduction
Combined Approach	Colon Cancer Diagnosis

2.4. Ant Colony Optimization Algorithm

Ants are observed to exhibit intelligent foraging behavior, allowing them to find optimal food sources and minimize the distance traveled. Inspired by this behavior, this study introduces a modified ACO-PSO algorithm to achieve optimal results [28][29].

First, a graphical model is introduced to represent all the features in the dataset. The graphical model is a network of interconnected nodes, where each node represents a feature. Then, the quantity of ants and the number of iterations is established [29]. The parameter τ represents the pheromone trail, and its initial value is set to 1 for all attributes. The parameter η represents heuristic information, and it is inversely proportional to the distance between attributes [30] [31]. Once the initial values are determined, the ACO-PSO algorithm can be applied. At each step, an ant is assigned a random node. To define the subsequent node, the transition probability is applied, which is given by Equation (1):

$$P_i^k(t) = \frac{|\tau_i(t)|^{\alpha} * |\eta_i(t)|^{\beta}}{\sum_{u \in j^k} |\tau_i(t)|^{\alpha} . |\eta_i(t)|^{\beta}} \; if(q > q_0) \quad (1)$$

$$j = \max_{u \in j^k} (\tau_i(i)^{\alpha} . \eta_i(i)^{\beta}) \; if(q < q_0) \quad (2)$$

The values of τ and η are adjusted to enhance their effectiveness by determining the values of α and β. The set j^k represents the traits that the ant has not yet encountered, with a value of zero assigned to traits previously observed by the ant. The parameter q_0 significantly influences the selection process, impacting both the greedy and probabilistic methods. q is a random number between 0 and 1.

When the nth ant completes node scanning, update node pheromone levels using Equation (3):

$$\tau_i(t+1) = (1-\rho)\tau_i(t) + \sum_{i=1}^{n} \Delta\tau_i^k(t) \quad (3)$$

The parameter ρ needs to be established to mitigate its impact. $\Delta\tau_i^k$ represents the inverse of the error achieved using the Wrapper method and corresponds to the number of nodes chosen on average in the Filter method [31].

2.5. Feature Selection with the Particle Swarm Optimization Algorithm

Scientists have long believed that birds use celestial bodies such as the moon, sun, and stars to navigate during

migration. However, recent research has shown that birds initially fly in random directions. Then, through interactions with each other, they agree on a common path. This suggests that bird migration is a collective effort involving the movement of large groups of birds. [32][33][34][35].

The goal of particle swarm optimization (PSO) is to discover the best solution for the entire swarm and each particle. PSO achieves this by modifying the positions and velocities of particles throughout the optimization process. Equations rooted in the velocity equation provided below are employed to update particle positions and velocities iteratively, with the introduction of uniform random variables ranging from 0 to 1 to introduce stochastic variation.

In this context, the inertia factor is represented by vi, k, and α stands for the self-confidence learning parameter, while β denotes the swarm influence learning parameter. At the same time, r1 and r2 are random variables ranging from 0 to 1. Also, vi, k corresponds to the velocity of particle i during iteration k. It's worth noting that particle i has never surpassed a more favorable state than PB, and no member of the population has ever attained a more superior state than GB. The position of the particle is denoted as xi, k. Therefore, this algorithm can be formulated as follows:

$$v_{t+1} = v_t + \varphi_1\beta_1(p_i - x_i) + \varphi_1\beta_1(p_g - x_i) \quad (4)$$

$$v_{i,k+1} = w * v_{i,k} + \alpha * r_1 * (PB - x_{i,k}) + \beta * r_2 * (GB - x_{i,k}) \quad (5)$$

$$x_{t+1} = v_t + v_{t+1} \quad (6)$$

$$x_{i,k+1} = x_{i,k} + v_{i,k} \quad (7)$$

In Figure 1, the diagram illustrates the updating of particle locations and velocities, where Pi represents the best local outcome, and Pg represents the optimal global outcome. Extensive research conducted by Hassan et al. [36][37] demonstrates that particle swarms exhibit a notably faster and more efficient convergence toward similar solutions when compared to genetic algorithms.

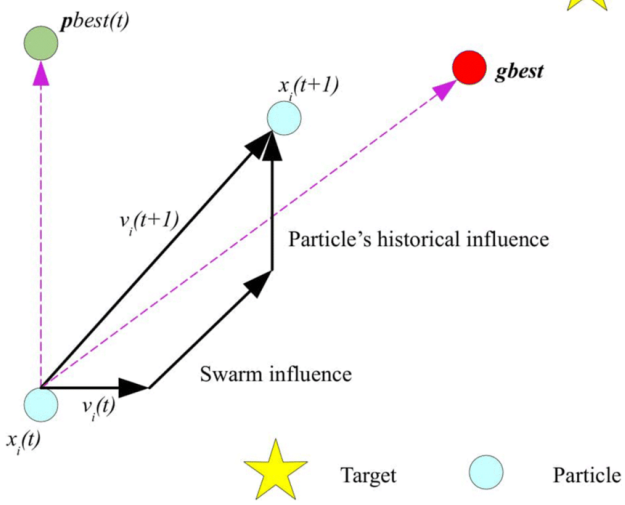

Figure 1. Diagram Illustrating Velocity and Position Updates in PSO[36]

The lower and upper bounds of the search area determined the constriction parameter. The maximum number of iterations in the proposed PSO-based method has been set as a variable. Figure 2 illustrates the flowchart of the algorithm, providing an overview of how it operates.

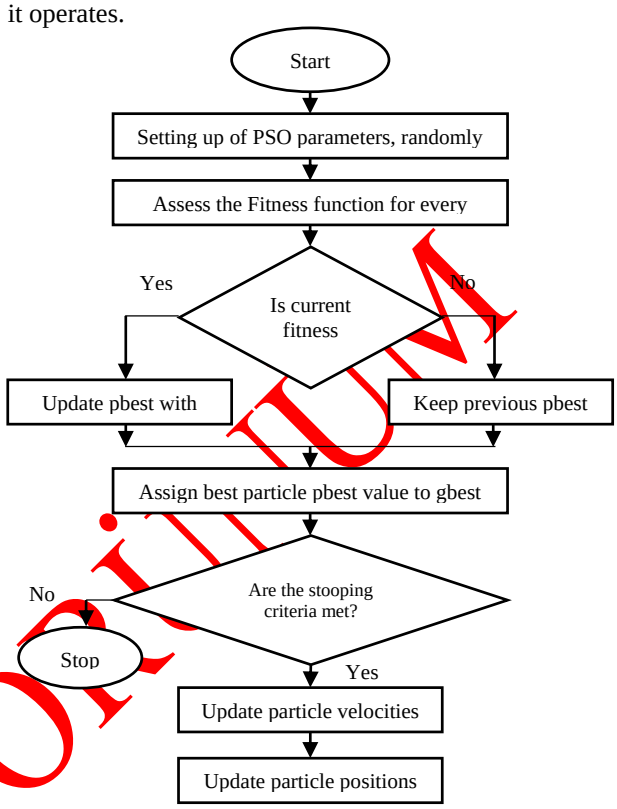

Figure 2. Diagrammatic Representation of PSO Algorithm

The equation of the PSO algorithm is presented below [38]:

$$v_i^d(t+1) = wv_i^d(t) + c_1r_1\left(\text{pbest}_i^d(t) - x_i^d(t)\right) + c_2r_2\left(\text{gbest}^d(t) - x_i^d(t)\right) \quad (8)$$

Throughout each iteration, every particle receives two 'best' values as updates. In this context, 'v' represents velocity, constrained by the limits set by ' $wmax$', and ' $wmin$ ', where 'w' stands for inertia weight, and 'x' represents the solution. Furthermore, 't' corresponds to the number of iterations, 'I' signifies the practicality of order within the population, and the search space is denoted by 'd'. 'c1' and 'c2' represent the acceleration factors, while 'r1' and 'r2' independently generate random values. In the context of PSO, the global solution is a record of the optimal outcome achieved so far by any particle across the entire population, while 'pbest' represents an individual particle's personal best solution, reflecting its own best result.

Following this step, as indicated in the subsequent formula, the velocity is transformed into a probability value:

$$s\left(v_i^d(t+1)\right) = \frac{1}{1+\exp\left(-v_i^d(t+1)\right)} \quad (9)$$

The practical position and ' $pbest$ ' in relation to '$gbest$' are transformed using these equations:

$$x_i^d(t+1) = \begin{cases} 1, & \text{if rand} < S\left(v_i^d(t+1)\right) \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

Where $rand$ is a random number between 0 and 1.

$$\text{pbest}_i(t+1) = \begin{cases} x_i(t+1), & \text{if } F(x_i(t+1)) < F\left(\text{pbest}_i(t)\right) \\ \text{pbest}_i(t), & \text{otherwise} \end{cases} \quad (11)$$

$$g \text{ best } (t+1) = \begin{cases} p_{\text{best}\,i}(t+1), \text{ if } F(\text{pbest}_i(t+1)) < F(\text{gbest}(t)) \\ \text{gbest}(t), \text{ otherwise} \end{cases} \quad (12)$$

Where F the Fitness function.

$$w = w_{max} - (w_{max} - w_{min})\left(\frac{t}{T_{max}}\right) \quad (13)$$

2.6. Enhancing Colon Cancer Diagnosis Accuracy Through Autoencoder-PSO Integration

In the initial phase of the research, the utilization of the Autoencoder and PSO algorithm aimed to refine the precision of colon cancer diagnosis by extracting and minimizing features, respectively. This process can be elaborated upon and visualized as follows: Utilizing the Autoencoder for Dataset Processing: Initially, the dataset about colon illness underwent processing through the Autoencoder. This neural network, designed for unsupervised learning, was entrusted with the task of distilling pertinent features from the input images depicting colon tissues. Through iterative training, the Autoencoder acquired the ability to condense the input data into a lower-dimensional latent space representation, capturing crucial features while excluding extraneous noise or irrelevant data. Dimensionality Reduction via the PSO algorithm: After feature extraction by the Autoencoder, the subsequent step involved the reduction of feature space dimensions using the PSO algorithm. The PSO algorithm, a hybrid optimization technique amalgamating principles from ACO and PSO, aimed to systematically explore and select the most informative subset of features from the multi-dimensional feature space. Drawing inspiration from collective intelligence observed in ant foraging behavior and bird migration swarm behavior, PSO iteratively refined the feature subset to concentrate on the most distinctive attributes associated with colon disease. Integration of Methodologies: The features extracted by the Autoencoder were then input into the PSO algorithm, which methodically honed the feature subset. This integrated approach was geared towards augmenting the accuracy and efficiency of colon cancer diagnosis by reducing the dimensionality of the feature space while retaining pertinent discriminative information. Through the synergistic utilization of both the Autoencoder and PSO, the model demonstrated adeptness in effectively discerning and categorizing histopathological images of colon tissues, resulting in elevated accuracy rates across diverse evaluation metrics. To summarize, the initial phase of the experimental investigation encompassed the preprocessing of the colon disease dataset utilizing the Autoencoder for feature extraction, followed by dimensionality reduction of the feature space via the PSO algorithm. This concerted methodology facilitated the precise classification of colon disease images, thereby contributing to the advancement of diagnostic accuracy and ultimately, patient care outcomes.

2.7. Reduction and Features

In the scenario where ACO-PSO collaborated with the Autoencoder, the process involved utilizing the Autoencoder for feature extraction and ACO-PSO for feature reduction. Here's a more detailed explanation of how ACO-PSO was merged with the Autoencoder:

Utilizing the Autoencoder for Feature Extraction: Initially, the dataset associated with colon illness underwent processing by the Autoencoder. An Autoencoder, a type of neural network used for unsupervised learning, aims to acquire efficient representations of input data. In this instance, the Autoencoder extracted pertinent features from images of colon tissues. Trained to condense input data into a lower-dimensional latent space representation, the Autoencoder captured significant features while filtering out noise or extraneous information.

Employing ACO-PSO for Feature Reduction: Following feature extraction using the Autoencoder, the subsequent step involved reducing the dimensionality of the feature space through ACO-PSO. ACO-PSO, a hybrid optimization algorithm combining ACO and PSO techniques, aims to effectively explore and select the most informative subset of features from the high-dimensional feature space.

Integration of Techniques: The features extracted by the Autoencoder were inputted into the ACO-PSO algorithm, which systematically refined the feature subset to focus on the most distinguishing attributes pertinent to colon disease. Leveraging the collective intelligence inspired by ant foraging behavior and swarm behavior observed in bird migrations, ACO-PSO efficiently searched for the optimal feature subset that optimized classification performance.

Classification: Upon completing the feature reduction process, the reduced feature set served as input for various classifiers to categorize the colon disease images. In this scenario, six different classifier types were employed, including Decision Tree, SVM, KNN, Ensemble, and Naive Bayes. These classifiers were evaluated based on metrics such as accuracy, true positive rate (TPR), true negative rate (TNR), false positive rate (FPR), false negative rate (FNR), precision (PPV), negative predictive value (NPV), F1-score, and misclassification rate (MR).

In summary, the integration of ACO-PSO with the Autoencoder involved using the Autoencoder for feature extraction to obtain a high-dimensional feature representation of colon disease images, followed by ACO-PSO for feature reduction to select the most informative subset of features. This collaborative approach aimed to enhance the accuracy and efficiency of colon cancer diagnosis by reducing the dimensionality of the feature space while retaining relevant discriminative information.

2.8. Crafting a Tailored Pre-Trained ResNet-50 Architecture for Colon Cancer Detection Using ACO-PSO

The development of the pre-trained ResNet-50 architecture using ACO-PSO adheres to a methodical approach:

- The setup phase involves initializing parameters for the ACO-PSO algorithm and preparing the dataset.
- Iterative refinement occurs, where adjustments to pheromone levels and heuristic information are made to enhance feature selection.
- The process focuses on selecting a subset of features that are most relevant for diagnosing colon cancer.
- The pre-trained ResNet-50 model is constructed, incorporating the chosen feature subset as input.
- The model undergoes training to fine-tune its parameters, optimizing its ability to classify colon cancer effectively.
- Validation and evaluation procedures are employed to gauge the model's performance, utilizing various metrics to ensure accurate diagnosis of colon cancer from histopathological images.

In essence, this structured methodology ensures the development of a ResNet-50 model tailored specifically for colon cancer detection, striking a balance between feature relevance and computational efficiency.

2.9. Optimizing Colon Cancer Detection: Developing Pre-Trained GoogLeNet Architecture with ACO-PSO

The creation of the pre-trained GoogLeNet architecture based on ACO-PSO followed a systematic process to optimize feature selection for colon cancer detection. Here's a detailed explanation of how this architecture was developed:

Initialization and Dataset Preparation: The process commenced with initializing parameters for the ACO-PSO algorithm and preparing a dataset containing histopathological images relevant to colon cancer. This dataset ensured comprehensive coverage of both cancerous and non-cancerous tissues.

Iterative Refinement: Through iterative refinement, the ACO-PSO algorithm adjusted pheromone levels and heuristic information, optimizing feature selection for colon cancer diagnosis. This iterative process ensured the selection of the most informative subset of features.

Feature Subset Selection: Utilizing the ACO-PSO algorithm, the most relevant features for colon cancer diagnosis were selected from the high-dimensional feature space. This prioritized selection process focused on discriminative features associated with colon disease, thereby enhancing the accuracy of the diagnostic model.

Construction of Pre-trained GoogLeNet Model: The selected feature subset served as input for constructing the pre-trained GoogLeNet architecture. Leveraging GoogLeNet's robust feature extraction capabilities, this architecture extracted intricate patterns and abnormalities from colon tissue images effectively.

Training and Fine-tuning: The constructed GoogLeNet model underwent training to fine-tune its parameters for accurate colon cancer classification. This training process optimized the model's ability to classify histopathological images of colon tissues, further enhancing diagnostic accuracy.

Validation and Evaluation: The performance of the pre-trained GoogLeNet model was validated and evaluated using various metrics such as accuracy, sensitivity, specificity, precision, F1-score, and misclassification rate. These metrics assessed the model's effectiveness in accurately diagnosing colon cancer from histopathological images.

In summary, the creation of the pre-trained GoogLeNet architecture based on ACO-PSO involved parameter initialization, iterative refinement of feature subsets, selection of relevant features, construction of the GoogLeNet model, training, and validation. This systematic approach ensured the tailored development of a GoogLeNet model optimized specifically for colon cancer detection, thereby improving diagnostic accuracy and patient outcomes.

2.10. Dataset

The dataset likely contains a collection of histopathological images specifically related to lung and colon cancer [39]. Images in the dataset are expected to be microscopic views of tissue samples obtained from lung and colon cancer patients. These images may show the cellular and tissue-level details of cancerous changes. Pathologists use such images to identify cancer cells, assess the degree of malignancy, and understand the histological characteristics of tumors. The dataset may include annotations or labels indicating regions of interest, such as areas with cancerous cells, normal tissue, and potentially other features relevant to diagnosis and research. The dataset may encompass different subtypes of lung and colon cancer, considering the histological diversity within these cancer types. Image resolution and size can vary, but they are likely to be high-resolution images to enable detailed analysis. Information such as patient demographics, clinical history, and potentially treatment outcomes might be included in the dataset. This additional data can be valuable for comprehensive research and analysis [39].

3. RESULTS and DISCUSSION

3.1. Classification Using Learnable Classifiers for PSO

To determine the ideal combination of techniques, a thorough investigation was done. An autoencoder method and a PSO algorithm were employed collaboratively on datasets associated with colon disease to isolate and choose the most critical attributes from the input training dataset. The identical datasets used in the first model were categorized using a pre-trained CNN in conjunction with the PSO method. A number of important metrics, such as accuracy, F1-score, etc., were applied to assess the performance of methods created

from the confusion matrix. For multiclass classification, the following metrics are used: total accuracy, class detection rate, and class FP rate. Our basic terms are False Positive (FP), True Positive (TP), True Negative (TN), and False Negative (FN), which stand for positive and negative classifications, respectively.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (14)$$

$$Sensitivity\ (True\ Positive\ Rate\ (TPR)) = \frac{TP}{TP+FN} \times 100\% \quad (15)$$

$$Specificity\ (True\ Negative\ Rate(TNR)) = \frac{TN}{TN+FP} \times 100\% \quad (16)$$

$$Precision\ (positive\ predictive\ value\ (PPV)) = \frac{TP}{TP+FP} \times 100\% \quad (17)$$

$$Negative\ predictive\ value\ (NPV) = \frac{TN}{TN+FN} \times 100\% \quad (18)$$

$$F1-score = \frac{2PPV \times TPR}{PPV+TPR} \times 100\% \quad (19)$$

3.2. Using Auto-Encoder with PSO for Colon Disease Dataset

Various scenarios were developed and assessed to validate the effectiveness of the proposed technique and to compare different combinations. In the initial stage, a dataset related to colon illness was processed by the Autoencoder, along with six different classifier types. The outcomes of the colon illness dataset using the Autoencoder and the PSO algorithm are presented in Table 4.

The most crucial factor in assessing this classification model is accuracy, which is based on the true values of the tested images that were classified. The SVM classifier achieved a higher accuracy rate of 79.21%, resulting in an error rate of 2.41%.

3.3. Using Auto-Encoder with ACO-PSO for Colon Disease Dataset

Using this second well-known dataset for colon disorders, which includes five distinct classes (non-cancer lung tissue, Squamous cell carcinoma of the lung, Adenocarcinoma of the lung, non-cancer colon tissue, and Adenocarcinoma of the colon), the model successfully classified medical images. Table 5 presents the outcomes obtained from the Autoencoder applied to the colon disease dataset with the utilization of the ACO-PSO algorithm.

The Ensemble classifier achieved 82.76% accuracy in the categorization of the classes of the ACO-PSO algorithm for selecting optimal features.

3.4. Pre-trained CNN with ACO-PSO for Colon Disease Dataset

The assessment of pre-trained CNN with ACO-PSO was conducted using the dataset related to colon diseases. Figure 3 illustrates the diagnostic rates for colon disease within this model. The simulation outcome, employing the ant colony optimization method in conjunction with the pre-trained ResNet-50 network, is presented in Figure 3.

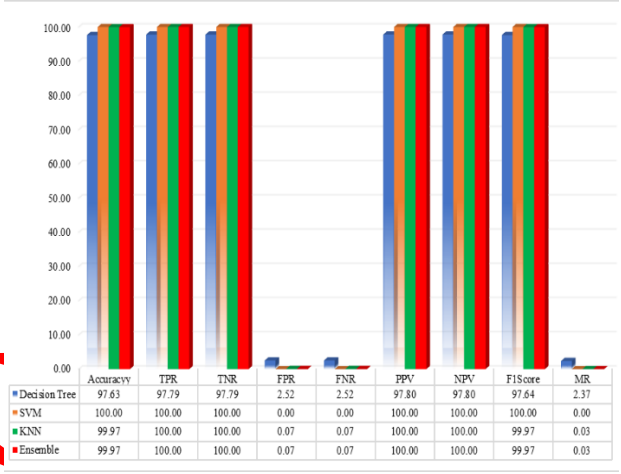

Figure 3. The result of the simulation based on the ResNet-50 and ACO-PSO

Table 4. Dataset on colon disease auto-encoder using PSO feature selection algorithm.

Method	ACC	TPR	TNR	FPR	FNR	PPV	NPV	F1-scoce	MR (Misclassification Rate)
Decision Tree	68.61	68.75	68.75	33.15	33.15	69.01	69.01	68.74	3.01
SVM	79.21	74.64	74.64	35.83	35.83	80.61	80.61	72.44	2.41
KNN	76.16	77.86	77.86	26.96	26.96	79.31	79.31	76.91	5.46
Ensemble	73.81	75.44	75.44	29.23	29.23	77.11	77.11	74.67	7.81
Naive Bayes	67.41	73.55	73.55	37.74	37.74	80.91	80.91	71.38	4.21

Figure 3 illustrates that the accuracy for the decision tree, SVM, KNN, and ensemble methods has been achieved at 97.63%, 100.00%, 99.97%, and 99.97%, respectively. The SVM classification method achieved 100% accuracy, which was the best result. SVMs are linear classifiers that are more accurate than other methods such as KNN, decision trees, and ensemble methods. Additionally, in this scenario, the highest accuracy was achieved using the SVM classifier with features that were obtained using the ACO-PSO algorithm and a pre-trained

Table 5. Using autoencoder and ACO-PSO feature selection for the colon disease dataset.

Method	ACC	TPR	TNR	FPR	FNR	PPV	NPV	F1-score	MR
Decision Tree	78.86	79.1	79.1	32.99	32.99	79.51	79.51	79.07	21.95
SVM	78.41	84.21	84.21	36.71	36.71	90.81	90.81	81.98	22.4
KNN	82.36	83.47	83.47	30.27	30.27	84.81	84.81	83.04	18.45
Ensemble	82.76	84.96	84.96	30.69	30.69	87.31	87.31	83.98	28.05
Naive Bayes	74.56	89.28	89.28	31.75	31.75	100.41	100.41	82.01	26.25

ResNet-50 network. Additionally, this study assessed the performance of decision tree, SVM, KNN, and ensemble methods with the F1 score metric, yielding scores of 99.50%, 99.93%, 99.97%, and 99.97%, respectively. As seen from the F1 score result, it can be understood that the KNN and Ensemble have the highest accuracy than

Table 6. Validation results of colon cancer diagnosis model

Category	Description
Different Datasets	1- Employed datasets related to colon disease 2- Included datasets specifically related to lung and colon cancer 3- Diverse range of histopathological images: non-cancerous lung/colon tissues, various cancerous tissues
Purpose	1-Evaluate model performance across different scenarios and datasets 2-Assess the generalizability of the model
Different Methodologies	1- Feature extraction and classification techniques: autoencoders, CNNs, ACO-PSO algorithms. 2-Classifiers: decision trees, SVM, KNN, ensemble methods
Purpose	1-Evaluate model robustness and generalizability across different approaches 2-Assess feature selection and classification impact
Validation Metrics	1-Accuracy, sensitivity, specificity, precision, F1-score, misclassification rate
Purpose	1-Provide comprehensive insights into model performance 2-Understand performance across datasets and methodologies
Consistency of Results	1-Reported consistent and high levels of accuracy and other metrics across experiments 2- Example: SVM classifier achieved 100% accuracy in a scenario 3-Other classifiers also demonstrated high performance

97.64%, 100.00%, 99.97%, and 99.97% for these algorithms, respectively. As seen from the F1 score results it can be understood that the SVM has higher accuracy than other methods. The mismatch ratio for the SVM, using ResNet-50 and ACO-PSO, is recorded as 0%.

The simulation results, based on the ACO-PSO method in conjunction with the pre-trained GoogLeNet network, are depicted in Figure 4.

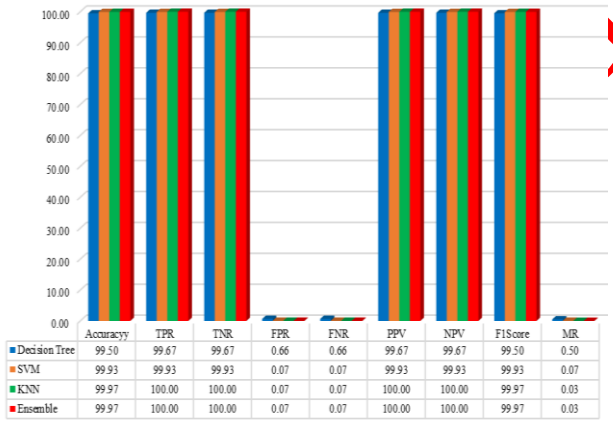

Figure 4. Simulation result based on the GoogLeNet with ACO-PSO

As shown in Figure 4, the accuracy for the decision tree, SVM, KNN, and ensemble methods has been obtained as 99.50%, 99.93%, 99.97%, and 99.97%, respectively. The best result for accuracy is 99.97%, obtained from the KNN and Ensemble classifier methods. In this scenario, the KNN and ensemble method has higher performance than other methods. In this scenario, it can be understood that the classification with KNN and Ensemble and the features obtained by using the ACO-PSO and pre-trained network with the GoogLeNet the highest accuracy has been obtained. In this study also, the F1 score has been implemented, and the result for the decision tree, SVM, KNN, and Ensemble methods has been obtained as other methods. The mismatch ratio for the KNN and Ensemble based on the GoogLeNet and ACO-PSO has been obtained as 0.03%.

Table 6 presents an overview of the validation outcomes of the colon cancer diagnosis model, covering various aspects of the research methodology and findings. It delineates the utilization of diverse datasets, methodologies, and validation criteria to assess the model's effectiveness and generalizability in identifying colon cancer.

The aim of examining different datasets is to assess the model's performance across various scenarios and data sources, including those relevant to lung and colon cancer. These datasets encompass a wide range of histopathological images, including both cancerous and non-cancerous tissues from the lung and colon.

Regarding methodologies, the study employed feature extraction and classification techniques such as autoencoders, CNNs, and ACO-PSO algorithms. Various classifiers, including decision trees, Support Vector Machines (SVM), KNN, and ensemble methods, were utilized to assess the model's resilience and adaptability across different approaches. This evaluation aims to understand how feature selection and classification methods impact the model's performance.

Validation metrics, such as accuracy, sensitivity, specificity, precision, F1-score, and misclassification rate, were employed to provide comprehensive insights into the model's effectiveness. These metrics help in understanding how the model performs across diverse datasets and methodologies.

The consistency of results is emphasized, indicating consistent and high levels of accuracy and other metrics across experiments. For instance, the SVM classifier achieved 100% accuracy in a specific scenario, highlighting the efficacy of the model. Other classifiers also demonstrated high levels of performance, further emphasizing the reliability of the proposed method.

In summary, through the utilization of diverse datasets, methodologies, and validation metrics, the study aimed to thoroughly evaluate the generalizability and efficacy of the proposed model for diagnosing colon cancer.

4. LIMITATIONS or CHALLENGES

Data Quality and Quantity: A primary hurdle in any machine learning investigation, particularly in medical imaging, is securing access to sufficient quantities of high-quality data. Specifically, histopathological images necessitate meticulous annotation and validation by expert pathologists. Limited or inferior data could introduce bias or inaccuracies during model training, thereby impacting the model's performance and its ability to generalize effectively in diagnosing colon cancer.

Feature Extraction and Selection: Despite the effectiveness of CNNs in extracting features from intricate medical images, the selection of the appropriate CNN architecture and feature extraction process is critical. Choosing unsuitable CNN architectures or inadequately optimizing feature selection methods might lead to subpar feature representation, consequently affecting the accuracy of the diagnostic model.

Algorithmic Complexity: Incorporating metaheuristic optimization algorithms such as ACO and PSO with CNNs introduces additional complexity to the model. Fine-tuning hyperparameters, like pheromone levels in ACO and inertia weight in PSO, demands careful consideration and may impact the optimization process's convergence and effectiveness.

Interpretability and Explain ability: Deep learning models, including CNNs, often lack interpretability and explain ability. This is particularly problematic in medical contexts where understanding the model's decision-making process is crucial for clinical decision-making. Ensuring transparency and interpretability in the model's decision-making process is vital for its acceptance and integration into clinical settings.

Generalization and Robustness: Evaluating the model's ability to generalize across diverse datasets and populations is essential. Overfitting to training data or failing to capture variations in disease presentation may compromise the model's robustness and real-world applicability. Comprehensive validation across multiple datasets and rigorous evaluation under various conditions are necessary to establish the model's reliability.

Ethical Considerations and Bias: The deployment of AI-based diagnostic tools in healthcare raises ethical concerns regarding patient privacy, consent, and algorithmic bias. Biases present in training data or algorithmic decisions could disproportionately affect certain demographic groups, leading to healthcare outcome disparities. Addressing these ethical considerations and mitigating algorithmic biases are crucial for the responsible development and deployment of AI models in healthcare.

Clinical Validation and Regulatory Approval: Transitioning AI-based diagnostic models from research to clinical practice necessitates rigorous clinical validation and regulatory approval. Collaborating with healthcare institutions, conducting prospective clinical trials, and navigating regulatory pathways are resource-intensive processes. Ensuring the model's safety, efficacy, and compliance with regulatory standards is paramount for its adoption in clinical settings.

Computational Resources and Infrastructure: Training and deploying deep learning models, especially those involving large datasets and complex architectures, require substantial computational resources and infrastructure. Access to high-performance computing resources and expertise in managing and scaling computational workflows are crucial for conducting large-scale studies and deploying AI models in real-world healthcare environments.

Addressing these challenges mandates interdisciplinary collaboration among clinicians, data scientists, ethicists, and regulatory experts to develop robust, interpretable, and ethically sound AI-based diagnostic tools for enhancing colon cancer diagnosis and patient care

5. CONCLUSION

Colorectal cancer is the third most deadly cancer in the world. Benign adenomatous polyps may bring on CRC, sometimes referred to as adenomas, which can subsequently transform into malignant polyps. The current suggested strategy for reducing mortality from CRC is routine screening for polyps, and colonoscopy is the preferred screening tool. To identify Cologne illness regions, this article tries to integrate human learning and training with machine learning techniques, like neural network learning. The ACO-PSO algorithm in the suggested method initially improves the precision of the ACO-PSO technique for choosing the specified characteristic by the optimization teaching and learning process. Then, using learning based on the neural network, the disease-affected areas are divided. The component reduction method has also been employed in this paper to enhance the knowledge and information in the image.

DECLARATION of ETHICAL STANDARDS

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Amna Ali A. Mohamed1, and Raheleh Ghadami: Performed the experiments and analyse the results and Wrote the manuscript.

Aybaba Hançerlioğullari, and Javad Rahebi: Perofrmed the experiments and analyse the results.

CONFLICT of INTEREST

There is no conflict of interest in this study.

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