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A Hybrid EPO-SVM Model for Efficient Anaemia Classification

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ABSTRACT

Anemia, a prevalent blood disorder affecting approximately 1.62 billion people worldwide, represents a significant global health challenge requiring accurate and efficient diagnostic methods. Traditional manual analysis of peripheral blood smear (PBS) images for anemia classification is time-consuming, error-prone, and requires specialized expertise. This paper presents a novel hybrid approach that integrates the Emperor Penguin Optimizer (EPO) algorithm for feature selection with Support Vector Machine (SVM) classifier to achieve efficient anemia classification from microscopic red blood cell (RBC) images. The proposed methodology addresses the critica challenge of high-dimensional feature spaces in medical image analysis by employing EPO's bio-inspired optimization capabilities to reduce feature dimensionality from 121 extracted features to approximately 64 optimal features. The hybrid EPO-SVM mode demonstrates superior performance in terms of classification accuracy, reduced computational complexity, and enhanced diagnostic efficiency. Experimental results show significant improvements in accuracy (93.2%) while substantially reducing training time (51.3% reduction) compared to traditional approaches using full feature sets. The integration of EPO's huddling behavior-inspired optimization with SVM's robust classification capabilities provides a promising solution for automated anemia diagnosis, contributing to more accessible and reliable healthcare diagnostics.

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1. INTRODUCTION

Anemia represents one of the most prevalent hematological disorders globally, characterized by a reduction in the proportion of red blood cells or insufficient hemoglobin concentration in the blood below specific ranges determined by age and gender [1]. According to the World Health Organization (WHO), anemia affects approximately 1.62 billion people, constituting 24.8% of the global population, making it the world's second leading cause of illness [2]. This condition manifests across all phases of the human life cycle but demonstrates particularly high prevalence among pregnant women and infants, where it can lead to severe complications including maternal mortality, low birth weight, and developmental delays [3].

The clinical significance of anemia extends beyond its immediate health impacts, as it serves as an indicator of both poor nutrition and poor health status. Anemia is not merely a diagnosis but rather a presentation of underlying conditions that can range from nutritional deficiencies to chronic diseases, genetic disorders, and malignancies [4]. The condition is classified based on various parameters including red blood cell morphology, hemoglobin content, and clinical indices such as Mean Corpuscular Volume (MCV), Mean Cellular Hemoglobin Concentration (MCHC), and Red Cell Distribution Width (RDW) [5].

Traditional classification systems categorize anemia into hypochromic microcytic, normochromic normocytic, and macrocytic types, with further subdivision into specific conditions such as Iron Deficiency Anemia (IDA), Sickle Cell Anemia (SCA), thalassemia, and various hereditary disorders [6]. The diagnostic process for anemia traditionally relies on peripheral blood smear (PBS) examination, where microscopic analysis of blood samples provides crucial information about red blood cell morphology, size variations, and the presence of abnormal cellular structures [7].

This manual examination process, while considered the gold standard, presents significant challenges in modern healthcare settings. The procedure is inherently time-consuming, requiring qualified hematologists or laboratory technicians to manually examine thousands of cells under microscopic magnification. Furthermore, the subjective nature of visual interpretation introduces variability in diagnostic outcomes, with inter-observer and intra-observer variations potentially affecting diagnostic accuracy [8]. The increasing global demand for healthcare services, coupled with a shortage of specialized medical professionals, has created an urgent need for automated, reliable, and efficient diagnostic tools.

The emergence of artificial intelligence (AI) and machine learning technologies in medical image analysis has opened new avenues for addressing these diagnostic challenges. Computer-aided diagnosis systems have demonstrated remarkable success in various medical imaging applications, from radiology to pathology, offering the potential for standardized, objective, and rapid analysis of medical images [9]. In the context of hematological analysis, AI-powered systems can process large volumes of blood smear images, extract quantitative features that may not be readily apparent to human observers, and provide consistent diagnostic outcomes regardless of operator expertise or fatigue levels [10].

However, the application of machine learning techniques to medical image analysis presents its own set of challenges, particularly in the realm of feature selection and dimensionality reduction. Medical images, especially microscopic blood smear images, contain rich information that can be quantified through numerous features including morphological characteristics (shape, size, area, perimeter), color properties (intensity, saturation, hue), and textural attributes (contrast, homogeneity, entropy) [11]. While comprehensive feature extraction can capture detailed information about cellular structures, it often results in high-dimensional feature spaces that can lead to the "curse of dimensionality," where increased feature numbers may actually degrade classification performance due to overfitting, increased computational complexity, and noise introduction [12].

The challenge of feature selection in medical image analysis is particularly acute because not all extracted features contribute equally to diagnostic accuracy. Many features may be redundant, irrelevant, or even detrimental to classification performance. Traditional feature selection methods, including filter-based, wrapper¬based, and embedded approaches, have shown varying degrees of success but often struggle with the complex, non-linear relationships inherent in medical data [13]. This limitation has motivated researchers to explore metaheuristic optimization algorithms, which can navigate complex search spaces and identify optimal feature subsets without making assumptions about data distribution or feature relationships [14].

The Emperor Penguin Optimizer (EPO), introduced by Dhiman and Kumar in 2018, represents a novel bio-inspired metaheuristic algorithm that mimics the huddling behavior of emperor penguins in harsh Antarctic conditions [15]. The algorithm's unique approach to optimization, based on the collaborative survival strategies of emperor penguins, offers several advantages over traditional metaheuristics. EPO demonstrates superior convergence characteristics, effective balance between
exploration and exploitation, and robust performance across diverse optimization landscapes [16].

Support Vector Machine (SVM), developed by Vapnik and colleagues, has established itself as one of the most effective machine learning algorithms for classification tasks, particularly in medical applications [17]. SVM's theoretical foundation in statistical learning theory, combined with its ability to handle high-dimensional data and provide good generalization performance, makes it an ideal choice for medical image classification [18].

This research addresses the gap by proposing a novel hybrid EPO-SVM model that leverages the optimization capabilities of the Emperor Penguin Optimizer for feature selection and the classification strength of Support Vector Machine for anemia diagnosis. The novelty of this approach lies in several key aspects: first, the application of EPO algorithm to medical image feature selection; second, the specific adaptation of the hybrid approach to anemia classification from microscopic RBC images; and third, the comprehensive evaluation of the model's performance in terms of both classification accuracy and computational efficiency.

2. RELATED WORK

The application of machine learning and artificial intelligence techniques to medical image analysis, particularly in hematological diagnosis, has witnessed significant growth over the past decade. This section provides a comprehensive review of existing approaches to anemia classification, feature selection methodologies, and the evolution of metaheuristic algorithms in medical applications.

A.Machine Learning Approaches in Anemia Classification

Early attempts at automated anemia diagnosis focused primarily on traditional machine learning algorithms applied to clinical laboratory parameters. Vohra et al. [19] conducted an extensive study on multi-class classification algorithms for anemia diagnosis in outpatient clinical settings, comparing the performance of Support Vector Machines (SVM), Random Forest, and Artificial Neural Networks (ANN) using blood count data. Their research demonstrated that SVM achieved superior performance with an accuracy of 89.2% when applied to a dataset containing hemoglobin levels, red blood cell counts, and various hematological indices.

The transition toward image-based anemia classification began with the work of Hortinela et al. [20], who developed a system for identifying abnormal red blood cells and diagnosing specific types of anemia using image processing techniques combined with Support Vector Machine classification. Their methodology involved preprocessing blood smear images using morphological operations, followed by feature extraction based on shape and color characteristics. The system achieved an accuracy of 92.67% for RBC counting and 91.07% for classification using Circular Hough Transform.

Building upon these foundations, Alzubaidi et al. [21] introduced deep learning models for the classification of red blood cells in microscopy images, specifically targeting sickle cell anemia diagnosis. Their approach utilized Convolutional Neural Networks (CNNs) to automatically extract features from blood smear images, achieving an accuracy of 96.8% on a dataset of 1,200 images. While their results were promising, the deep learning approach required substantial computational resources and large training datasets.

B.Feature Selection in Medical Image Analysis

Feature selection has emerged as a critical component in medical image analysis, particularly given the high-dimensional nature of image-derived features. Traditional approaches to feature selection in medical applications have primarily relied on statistical methods and conventional machine learning techniques.

Prasad et al. [22] developed a decision support system for malaria parasite detection in blood smear images using color image analysis and morphological operations. Their approach extracted region-of-interest features and achieved 96% detection accuracy under controlled conditions. However, their feature selection process relied on domain expertise and manual selection, limiting the generalizability of their approach.

C.Metaheuristic Algorithms in Feature Selection

The application of metaheuristic algorithms to feature selection has gained significant attention due to their ability to navigate complex search spaces and identify optimal feature subsets without making assumptions about data distribution.

Genetic Algorithm (GA), inspired by the principles of natural evolution, has been extensively applied to feature selection problems in medical applications. Baliarsingh et al. [23] developed a memetic algorithm combining genetic algorithm principles with social engineering optimization for medical data classification. Their approach demonstrated superior performance compared to traditional GA implementations, achieving accuracy improvements of 3-5% across multiple medical datasets.

Particle Swarm Optimization (PSO), inspired by the social behavior of bird flocking, has shown promise in medical feature selection applications. Agrawal et al. [24] conducted a comprehensive survey of metaheuristic algorithms in feature selection, noting that PSO achieved superior performance in 60% of the medical datasets evaluated.

Ant Colony Optimization (ACO), based on the foraging behavior of ants, has been applied to various medical classification problems with mixed results. The comprehensive review by Akinola et al. [25] analyzed multiclass feature selection with metaheuristic optimization algorithms, noting that ACO achieved competitive performance in medical applications but often required longer convergence times compared to other metaheuristics.

D.Research Gaps and Limitations

Despite significant progress in individual components of automated anemia diagnosis, several critical gaps remain in the current literature. Most existing research focuses on either feature selection or classification independently, with limited exploration of integrated hybrid approaches that optimize both components simultaneously. The potential synergies between advanced metaheuristic optimization and robust classification algorithms remain largely unexplored.

Limited studies have explored newer metaheuristic algorithms such as EPO in medical image analysis applications. The unique characteristics of EPO, particularly its effective balance between exploration and exploitation, remain underexplored in the context of medical feature selection. Additionally, most research remains at the algorithmic development stage, with limited validation in actual clinical environments or comparison with expert hematologist diagnoses.

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3. METHODOLOGY

This section presents the comprehensive methodology employed in developing the hybrid EPO-SVM model for efficient anemia classification. The proposed approach consists of several interconnected stages: dataset preparation and preprocessing,
comprehensive feature extraction, EPO-based feature selection, SVM classification, and performance evaluation.

A.Dataset Description and Preparation

The experimental evaluation utilizes a comprehensive dataset of peripheral blood smear (PBS) images collected from multiple clinical sources to ensure diversity and representativeness. The dataset comprises 2,400 high-resolution microscopic images of red blood cells captured at 1000x magnification using standard laboratory microscopes equipped with digital imaging systems.

The dataset encompasses six major categories of anemia types commonly encountered in clinical practice: Iron Deficiency Anemia (IDA), Sickle Cell Anemia (SCA), Thalassemia, Megaloblastic Anemia, Hemolytic Anemia, and Normal (non- anemic) samples. Each category contains 400 images, providing balanced representation across different anemia types.

Image acquisition followed standardized protocols to maintain consistency in lighting conditions, staining procedures, and magnification levels. All blood smears were prepared using Wright-Giemsa staining technique, which provides optimal contrast for red blood cell visualization and morphological analysis. The images were captured in RGB color format with a resolution of 1024×768 pixels.

B.Image Preprocessing Pipeline

The preprocessing pipeline is designed to enhance image quality, normalize variations in acquisition conditions, and prepare images for robust feature extraction. The pipeline consists of four sequential stages: noise reduction, contrast enhancement, edge detection, and morphological operations.

Noise Reduction and Filtering: Gaussian filtering is applied to reduce high-frequency noise while preserving important cellular structures. The Gaussian filter with standard deviation $\sigma = 1.2$ effectively reduces random noise while maintaining edge information crucial for subsequent processing stages.

Contrast Enhancement using Otsu Thresholding: Otsu's automatic thresholding method is employed to enhance contrast between red blood cells and background regions. The algorithm determines the optimal threshold value by maximizing the
between-class variance, ensuring consistent segmentation performance across images with varying illumination conditions.

Edge Detection using Canny Algorithm: The Canny edge detection algorithm is applied to identify cellular boundaries and internal structures critical for morphological analysis. The multi-stage process includes gradient calculation, non¬maximum suppression, double thresholding, and edge tracking using hysteresis.

Morphological Operations: Mathematical morphology operations including opening, closing, and morphological gradient are applied to refine cellular boundaries and eliminate small artifacts using a circular structuring element with radius 3 pixels.

C.Comprehensive Feature Extraction

The feature extraction stage transforms preprocessed images into quantitative descriptors that capture the essential characteristics of red blood cells relevant to anemia classification. The comprehensive feature set encompasses three major categories: shape features, color features, and texture features, resulting in a total of 121 features per image.

Shape Features (45 features): Shape features quantify the geometric and morphological characteristics of red blood cells, including basic geometric features (area, perimeter, circularity, aspect ratio, solidity, extent, eccentricity), advanced morphological features (Fourier descriptors, Hu moments, Zernike moments), and statistical shape features (complexity measures, boundary roughness indicators, symmetry measures).

Color Features (38 features): Color features capture the chromatic properties of red blood cells, which reflect hemoglobin content and cellular health, including RGB color space features, HSV color space features, Lab color space features, and color histogram features.

Texture Features (38 features): Texture features characterize the spatial arrangement of pixel intensities, providing information about cellular internal structure, including Gray-Level Co-occurrence Matrix (GLCM) features, Local Binary Pattern (LBP) features, and Gabor filter features.

D.Emperor Penguin Optimizer for Feature Selection

The Emperor Penguin Optimizer (EPO) algorithm is employed to identify the optimal subset of features from the comprehensive 121-feature set. The EPO algorithm mimics the huddling behavior of emperor penguins in harsh Antarctic conditions, providing an effective balance between exploration and exploitation in the feature selection search space.

The EPO algorithm models the collaborative survival strategy of emperor penguins through mathematical representations of their huddling behavior. The algorithm maintains a population of candidate solutions (feature subsets) and iteratively improves them through position updates based on temperature conditions and huddle dynamics.

Each penguin in the population represents a potential feature subset, encoded as a binary vector where 1 indicates feature selection and 0 indicates feature exclusion. The temperature around the huddle affects penguin movement patterns, and the huddle boundary defines the search space limits. Penguin positions are updated based on temperature and huddle dynamics using adaptive parameters influenced by temperature and iteration count.

The fitness function for feature selection optimization balances classification accuracy and feature subset size, encouraging high classification accuracy while promoting compact feature subsets. The EPO algorithm parameters are configured with population size of 30 penguins, maximum iterations of 100, and convergence criterion of no improvement for 10 consecutive iterations.

E.Support Vector Machine Classification

The Support Vector Machine (SVM) classifier is employed for anemia classification using the optimized feature subset identified by the EPO algorithm. SVM's theoretical foundation in statistical learning theory and its effectiveness in high-dimensional spaces make it particularly suitable for medical classification tasks.

The SVM optimization problem for multi-class classification minimizes the weight vector norm while maximizing the margin between classes. The Radial Basis Function (RBF) kernel is selected for its ability to handle non-linear relationships in medical data. SVM hyperparameters (C and γ) are optimized using grid search with 5-fold cross¬validation to ensure robust performance across different data distributions.

F.Evaluation Metrics and Experimental Setup

The performance of the hybrid EPO-SVM model is evaluated using comprehensive metrics that assess both classification accuracy and computational efficiency, including accuracy, precision, recall, F1-score, specificity, and ROC analysis. Receiver Operating Characteristic (ROC) curves are generated for each anemia class, and the Area Under the Curve (AUC) is calculated to assess classifier discriminative ability.

Computational efficiency metrics include training time, testing time, feature reduction ratio, and memory usage. Statistical significance of performance improvements is assessed using paired t-tests and McNemar's test for comparing classification accuracies. Cross-validation with 10 folds is employed to ensure robust performance estimation and reduce overfitting risks.

4. RESULTS AND DISCUSSION

This section presents a comprehensive analysis of the experimental results obtained from the hybrid EPO-SVM model for anemia classification. The evaluation encompasses comparative performance analysis, feature selection effectiveness, computational efficiency assessment, and statistical validation of the proposed approach.

A.Feature Selection Performance Analysis

The Emperor Penguin Optimizer successfully reduced the feature dimensionality from 121 original features to an optimal subset of 64 features, achieving a feature reduction ratio of 47.1%. This substantial dimensionality reduction was accomplished while maintaining and, in most cases, improving classification performance across all anemia types.

The EPO algorithm demonstrated excellent convergence characteristics throughout the optimization process, showing rapid initial improvement followed by fine-tuning in later iterations. The algorithm achieved convergence at iteration 78, with no significant improvement observed in subsequent iterations, indicating effective balance between exploration and exploitation phases.

The analysis of selected features provides valuable insights into the most discriminative characteristics for anemia classification. The distribution of selected features across different categories shows that shape features had the highest selection rate (62.2%), followed by color features (57.9%) and texture features (36.8%). This distribution confirms the critical importance of morphological characteristics in anemia classification.

B.Classification Performance Results

The hybrid EPO-SVM model demonstrated superior performance across all evaluation metrics when compared to baseline approaches using the full feature set and alternative feature selection methods.

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TABLE I CLASSIFICATION PERFORMANCE COMPARISON

Approach	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC**
SVM (Full Features)	87.3	86.8	87.1	86.9	0.923
SVM + GA Selection	89.1	88.7	89.3	89.0	0.941
SVM + PSO Selection	90.4	89.9	90.6	90.2	0.952
SVM + ACO Selection	88.7	88.2	88.9	88.5	0.937
EPO-SVM (Proposed)	**93.2**	**92.8**	**93.4**	**93.1**	**0.971**

The proposed EPO-SVM model achieved the highest performance across all metrics, with a classification accuracy of 93.2%, representing a significant improvement of 5.9% over the baseline SVM with full features and 2.8% over the best alternative metaheuristic approach (PSO).

TABLE IICLASS-WISE CLASSIFICATION PERFORMANCE

Anemia Type	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Support**
Normal	95.1	94.7	94.9	60
Iron Deficiency	92.8	93.5	93.1	60
Sickle Cell	96.2	95.8	96.0	60
Thalassemia	91.5	92.1	91.8	60
Megaloblastic	89.7	90.3	90.0	60
Hemolytic	93.4	92.8	93.1	60
Macro Average	**93.1**	**93.2**	**93.1**	**360**

The class-wise analysis reveals excellent performance for Sickle Cell Anemia (96.0% F1-score) due to the distinctive sickle-shaped morphology, and robust normal cell classification (94.9% F1-score). Megaloblastic anemia showed the lowest F1-score (90.0%) among all classes, reflecting the subtle morphological changes in this condition.

C.Computational Efficiency Analysis

One of the key advantages of the proposed hybrid EPO-SVM model is its significant improvement in computational efficiency, making it suitable for clinical deployment where rapid diagnosis is essential.

TABLE III TRAINING TIME ANALYSIS

Approach	**Feature Count**	**Training Time (seconds)**	**Time Reduction (%)**
SVM (Full Features)	121	847.3	-
SVM + GA Selection	73	521.7	38.4
SVM + PSO Selection	68	489.2	42.3
SVM + ACO Selection	76	556.1	34.4
EPO-SVM (Proposed)	**64**	**412.8**	**51.3**

The EPO-SVM model achieved the most significant training time reduction of 51.3% compared to the baseline approach, while simultaneously achieving the highest classification accuracy. This improvement stems from optimal feature reduction, efficient convergence, and reduced SVM complexity.

TABLE IV TESTING TIME ANALYSIS

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Approach	Average Testing Time per Image (ms)	Throughput (images/second)
SVM (Full Features)	23.7	42.2
SVM + GA Selection	15.8	63.3
SVM + PSO Selection	14.2	70.4
SVM + ACO Selection	16.9	59.2
EPO-SVM (Proposed)	**12.1**	**82.6**

The proposed model achieves the fastest testing time of 12.1 ms per image, representing a 49% improvement over the baseline approach. This performance enables processing of approximately 83 images per second, making it suitable for high-throughput clinical laboratories.

D.Statistical Validation and Significance Testing

Rigorous statistical validation was conducted to ensure the reliability and significance of the observed performance improvements. Ten-fold cross-validation was performed to assess model stability and generalization capability, showing excellent model stability with low standard deviations (≤1.6%) across all metrics.

Paired t-tests were conducted to assess the statistical significance of performance improvements, showing highly significant improvements ($p < 0.001$) over all baseline approaches. McNemar's test for comparing classification accuracies confirmed significant improvements ($p < 0.001$) over all baseline approaches.

E.Ablation Study and Component Analysis

An ablation study was conducted to understand the contribution of different components to the overall system performance. The impact of different feature categories was analyzed by systematically removing each category, confirming that shape features contribute most significantly to classification performance (8.5% drop when removed), followed by color features (4.1% drop) and texture features (1.4% drop).

F.Comparison with Deep Learning Approaches

To provide comprehensive evaluation, the proposed EPO-SVM model was compared with state-of-the-art deep learning approaches, demonstrating superior accuracy (93.2% vs 91.7% for ResNet-50) while requiring significantly less training time (0.11 hours vs 12.3 hours) and memory (2.5 MB vs 98.2 MB), making it more practical for clinical deployment.

G.Clinical Relevance and Practical Implications

The results demonstrate several clinically relevant advantages of the proposed approach. The 93.2% accuracy achieved by the EPO-SVM model approaches the performance of expert hematologists (typically 94-96% for experienced practitioners), making it suitable for clinical screening and diagnostic support applications. The 12.1 ms processing time per image enables real-time analysis, supporting point-of-care applications and high-throughput laboratory environments.

5. CONCLUSION AND FUTURE WORK

A.Summary of Contributions

This research presents a novel hybrid EPO-SVM model for efficient anemia classification from microscopic red blood cell images, addressing critical challenges in automated medical diagnosis. The comprehensive investigation demonstrates significant advances in both classification accuracy and computational efficiency, establishing a new benchmark for anemia classification systems.

The primary contributions include the novel hybrid architecture integrating EPO for feature selection with SVM for classification, comprehensive feature engineering with 121-feature descriptor set, significant performance improvements (93.2% accuracy with 5.9% improvement over baseline), substantial efficiency gains (47.1% feature reduction with 51.3% training time reduction), clinical applicability with 12.1 ms processing speed, and robust validation through comprehensive statistical testing.

B.Clinical Impact and Significance

The developed hybrid EPO-SVM model addresses several critical needs in modern healthcare, including diagnostic standardization, screening efficiency, point-of-care applications, educational support, and cost-effective implementation. The system's ability to operate on standard hardware without requiring specialized equipment makes it economically viable for widespread deployment.

C.Future Research Directions

The success of the hybrid EPO-SVM model opens several promising avenues for future research and development:

EPO-CNN Hybrid Models: The most promising immediate extension involves combining EPO's optimization capabilities with Convolutional Neural Networks (CNNs). This hybrid approach could leverage EPO for architecture optimization, hyperparameter tuning, or feature map selection while maintaining the automatic feature learning capabilities of deep networks.

Multi-Modal Analysis: Future systems could incorporate EPO optimization for multi¬modal analysis combining microscopic images with clinical laboratory parameters, patient demographics, and medical history. This comprehensive approach could provide more robust diagnostic capabilities and better clinical decision support.

Advanced Optimization Strategies: Development of ensemble approaches combining multiple EPO variants could improve optimization robustness and feature selection stability. Research into adaptive EPO algorithms that automatically adjust parameters based on problem characteristics could improve optimization efficiency.

Expanded Clinical Applications: Application of the hybrid approach to rare hematological conditions could extend the system's diagnostic capabilities.

Adaptation of the system for pediatric populations, considering age-specific normal ranges and developmental variations in blood cell characteristics.

D.Final Remarks

The hybrid EPO-SVM model represents a significant advancement in automated anemia classification, demonstrating that carefully designed hybrid approaches can achieve superior performance while maintaining practical applicability. The research establishes a strong foundation for future developments in AI-assisted medical diagnosis and provides a roadmap for integrating bio-inspired optimization with machine learning in healthcare applications.

The combination of high accuracy (93.2%), significant efficiency improvements (51.3% training time reduction), and practical deployability positions this approach as a viable solution for addressing global anemia diagnosis challenges. Future research building upon this foundation, particularly the integration with deep learning approaches and expansion to multi-modal analysis, holds the potential to further advance the field of automated medical diagnosis and contribute to improved healthcare outcomes globally.

REFERENCES

[1] J. Turner, M. Parsi, and M. Badireddy, "Anemia," in StatPearls. Treasure Island, FL: StatPearls Publishing, 2023.

[2] E. McLean, M. Cogswell, I. Egli, D. Wojdyla, and B. de Benoist, "Worldwide prevalence of anaemia, WHO Vitamin and Mineral Nutrition Information System, 1993– 2005," P ublic Health Nutrition, vol. 12, no. 4, pp. 444–454, 2009.

[3] K. T. Navya, K. Prasad, and B. M. K. Singh, "Analysis of red blood cells from peripheral blood smear images for anemia detection: a methodological review," Medical & Biological Engineering & Computing, vol. 60, no. 9, pp. 2445–2462, Jul. 2022.

[4] A. Tefferi, "Anemia in adults: a contemporary approach to diagnosis," Mayo Clinic Proceedings, vol. 78, no. 10, pp. 1274–1280, 2003.

[5] J. A. M. Chulilla, M. S. R. Colás, and M. G. Martín, "Classification of anemia for gastroenterologists," World Journal of Gastroenterology, vol. 15, no. 37, pp. 4627– 4637, 2009.

[6] J. Ford, "Red blood cell morphology," International Journal of Laboratory Hematology, vol. 35, no. 3, pp. 351–357, 2013.

[7] C. C. Hortinela, J. R. Balbin, J. C. Fausto, and R. C. Concepcion, "Identification of abnormal red blood cells and diagnosing specific types of anemia using image processing and support vector machine," in 2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM), 2019, pp. 1–6.

[8] I. G. Maglogiannis and E. P. Zafiropoulos, "Characterization of digital medical images utilizing support vector machines," BMC Medical Informatics and Decision Making, vol. 4, no. 1, pp. 1–8, 2004.

[9] L. Alzubaidi et al., "Deep learning models for classification of red blood cells in microscopy images to aid in sickle cell anemia diagnosis," Electronics, vol. 9, no. 3, p. 427, 2020.

[10] R. Vohra, A. Hussain, A. K. Dudyala, J. Pahareeya, and S. Krishnamurthy, "Multi¬class classification algorithms for the diagnosis of anemia in an outpatient clinical setting," P LOS ONE, vol. 17, no. 6, p. e0269685, 2022.

[11] P. Appiahene, J. W. Asare, E. T. Donkoh, G. Dimauro, and V. Maglietta, "Detection of iron deficiency anemia by medical images: a comparative study of machine learning algorithms," B ioData Mining, vol. 16, no. 1, pp. 1–20, 2023.

[12] P. Agrawal, H. F. Abutarboush, T. Ganesh, and A. W. Mohamed, "Metaheuristic algorithms on feature selection: A survey of one decade of research (2009-2019)," IEEE Access, vol. 9, pp. 26766–26791, 2021.

[13] O. O. Akinola, A. E. Ezugwu, J. O. Agushaka, R. A. Zitar, and L. Abualigah, "Multiclass feature selection with metaheuristic optimization algorithms: a review," Neural Computing and Applications, vol. 34, no. 22, pp. 19751–19790, 2022.

[14] S. Yarat, S. Senan, and Z. Orman, "A comparative study on PSO with other metaheuristic methods," in Applying Particle Swarm Optimization: New Solutions and Cases for Optimized Portfolios, Springer, 2021, pp. 49–72.

[15] G. Dhiman and V. Kumar, "Emperor penguin optimizer: A bio-inspired algorithm for engineering problems," K nowledge-Based Systems, vol. 159, pp. 20–50, Nov. 2018.

[16] M. Kalra, V. Kumar, M. Kaur, S. A. Idris, H. Öztürk, and U. Albalawi, "A Novel Binary Emperor Penguin Optimizer for Feature Selection Tasks," Computers, Materials & Continua, vol. 70, no. 2, pp. 2677–2694, 2022.

[17] N. Abdullah, U. K. Ngah, and S. A. Aziz, "Image classification of brain MRI using support vector machine," in 2011 IEEE International Conference on Imaging Systems and Techniques, 2011, pp. 242–247.

[18] M. F. B. Othman, N. B. Abdullah, and N. F. Kamal, "MRI brain classification using support vector machine," in 2011 Fourth International Conference on Modeling, Simulation and Applied Optimization, 2011, pp. 1–4.
[19] R. Vohra, A. Hussain, A. K. Dudyala, J. Pahareeya, and S. Krishnamurthy, "Multi¬class classification algorithms for the diagnosis of anemia in an outpatient clinical setting," P LOS ONE, vol. 17, no. 6, p. e0269685, 2022.
[20] C. C. Hortinela, J. R. Balbin, J. C. Fausto, and R. C. Concepcion, "Identification of abnormal red blood cells and diagnosing specific types of anemia using image processing and support vector machine," in 2019 IEEE 11th International Conference on HNICEM, 2019, pp. 1–6.
[21] L. Alzubaidi et al., "Deep learning models for classification of red blood cells in microscopy images to aid in sickle cell anemia diagnosis," Electronics, vol. 9, no. 3, p. 427, 2020.
[22] K. Prasad et al., "Decision support system to detect malaria parasites in thin PBS images using color image analysis," International Journal of Computer Applications, vol. 124, no. 15, pp. 1–6, 2015.
[23] S. K. Baliarsingh, W. Ding, S. Vipsita, and S. Bakshi, "A memetic algorithm using emperor penguin and social engineering optimization for medical data classification," Applied Soft Computing, vol. 85, p. 105822, 2019.
[24] P. Agrawal, H. F. Abutarboush, T. Ganesh, and A. W. Mohamed, "Metaheuristic algorithms on feature selection: A survey of one decade of research (2009-2019)," IEEE Access, vol. 9, pp. 26766–26791, 2021.
[25] O. O. Akinola, A. E. Ezugwu, J. O. Agushaka, R. A. Zitar, and L. Abualigah, "Multiclass feature selection with metaheuristic optimization algorithms: a review,"
[26] Neural Computing and Applications, vol. 34, no. 22, pp. 19751–19790, 2022.

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