Whale Optimization-Driven Generative Convolutional Neural Network Framework for Anaemia Detection from Blood Smear Images

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***Abstract*—Anaemia is a frequent blood disorder marked by a reduction in the quantity of haemoglobin or the number of red blood cells in the blood. Quick and accurate anaemia detection is crucial for fast action and effective treatment. In this research, we provide a new structure called Whale Optimization-Driven Generative Convolutional Neural Network (WO-GCNN) for the detection of anaemia using blood smear pictures. To increase anaemia detection accuracy, the WO-GCNN system combines the strength of generative models and convolutional neural networks (CNNs). In order to create artificial blood smear images and learn the underlying data distribution, generative models, such as Generative Adversarial Networks (GANs), are used. Improve the functionality of the WO-GCNN system by applying the Whale Optimisation Algorithm (WOA), which is based on the hunting behaviours of humpback whales. To create the optimal set of CNN weights, the WOA effectively achieves a compromise between exploitation and exploration. The WO-GCNN framework accelerates convergence speed and increases overall performance of anaemia detection by incorporating the WOA into the training process. On a sizable dataset of blood smear pictures obtained from clinical settings, we assess the suggested WO-GCNN system. A highly accurate and effective approach for the early identification of anaemia is produced by combining generative models and CNNs with the WOA optimisation. By enabling early anaemia identification, the proposed WO-GCNN framework has the potential to have a substantial impact on the field of medical image analysis and enhance patient care. It can be a useful tool for medical personnel, supporting them in making decisions and giving anaemia patients urgent interventions.**

Keywords*—Generative adversarial network, blood smear images; convolutional neural network, anaemia; Whale Optimization

I. Introduction

The most prevalent haematological condition, defined as low haemoglobin concentration, affects over two billion individuals worldwide. Numerous acute and chronic diseases, including cancer, malnutrition, gastrointestinal bleeding, and chronic kidney disease, may trigger it. While severe anaemia, like thalassemia, require ongoing monitoring, others can be managed with simple medications. Some dangerous emerging reasons for anaemia, like significant gastrointestinal bleeding, necessitate early identification. Until the illness is not compensated and consequences arise, it is challenging to identify anaemia using simply patient records and examinations. The most common method for identifying anaemia is a complete blood count conducted in a laboratory. The laboratory test is intrusive, expensive, and needs specialised facilities and supplies (such as skilled medical personnel for blood sample and a haematology analyser for analysis using a biochemical reagent) [1].

The main factor contributing to anaemia, which typically has a high onset during preadolescence and happens if the blood's capacity for carrying oxygen is insufficient to satisfy the body's physiological needs, is a decline in red blood cell production. It is a significant issue in worldwide public health that necessitates the use of preventative diagnostic technologies. For adults, the lower recognised threshold for haemoglobin content in the blood is: 13.0 g/dL for males and 12.0 g/dL for women; tolerance levels due to varied races and ages should be taken into consideration. The creation of remedies intended at bolstering diagnosing concerns is the focus of the investigation discussed in this paper. To detect critical conditions, including the need for a donation of blood, or to allow autonomous tracking of haemoglobin levels, extremely precise instruments are needed. Lower equipment costs and convenience of use are also priorities in settings lacking surgeries and suitable instruments. Additionally, since non-invasive techniques enable the tracking of therapy answers, this technique is crucial for directing a more efficient and affordable tracking plan [2].

IDA, which is more prevalent in women, continues to be one of the five most common causes of years spent with a handicap in people. While it has historically been viewed primarily as a problem of public health impacting developing children, premenopausal women, and pregnant women, it is also coming to light as a clinical condition which may affect clients presenting across various healthcare and surgical fields, particularly those with chronic illnesses and older adults. International practise recommendations have been prompted to give special consideration to IDA assessment and treatment as new data on the role of IDA in poor medical results continues to emerge. The vague nature of the signs and the numerous IDA aetiologies, however, might make the diagnosis difficult. Additionally, the availability of several iron supplements formulas can make treatment choices more difficult [3].

According to the World Health Organisation (WHO), a patient blood management (PBM) strategy should be utilised to maximise the surgical patient's natural volume of blood. Several instructions, which include those for managing and optimising pre-operative anaemia and cells salvaging, have been published to aid hospitals in the execution of patient blood management. Studies have demonstrated that managing patient blood results in better outcomes and lower healthcare expenses [4]. Implementing patient blood management was found to reduce transfusions, hospitalisations, morbidity, and hospital readmission in total knee and hip arthroplasty and heart surgery. In one potential multi-centre study, the safety of a hospital-wide implementation of patient blood management was assessed. The outcomes of 54,513 patients prior to and 75,206 patients following the implementation of patient blood management showed that it was not disadvantaged. Data on the application of patient blood management in four tertiary institutions for 605,046 patients was provided by a sizable Australian study. A five-year implementation plan was started, and the last year's results were compared to the baseline years in terms of mortality, costs, and red cell transfusions. [5].

Red blood cells include the iron-containing protein known as haemoglobin, also known as Hgb or Hb, which is in charge of transporting oxygen from the respiratory system to other organs. Healthy adolescent blood haemoglobin levels for males and females normally fall between 14 to 18 g/dl and 12 to 16 g/dl, respectively. Blood sugar levels can, however, drop considerably due to a variety of illnesses, poor nutrition, and abnormalities of the bone marrow. Anaemia is a serious haematological condition that can lead to physical and mental weakness, mood swings, cognitive impairment, skin pallor, and in the worst cases, cardiac arrest. The World Health Organisation (WHO) has identified anaemia as a severe health concern for young children and expectant mothers. Invasive tests for blood are the most popular method of detecting anaemia and monitoring Hb levels. The intrusive blood tests are uncomfortable and run the danger of becoming infected while in the hospital. A visual inspection of other tissues in the body, such as the tongue, nail beds, palmar crease, and palpebral conjunctiva, is recommended in order to identify anaemia [6]. But a highly skilled medical professional who is able to connect the visual indicators to anaemia ought to just carry out such a test. Inspection by hand also carries the hazards of inter- and intra-observer bias, human error, and non-reproducible outcomes. As a result, there is a pressing need for automated tools to assist in the anaemia screening process. Recent developments in deep learning have brought efficient answers to issues in the biomedical sector. Additionally, they can be utilised to create sophisticated computer-aided diagnosis (CADx) tools that examine images of body components like the conjunctiva and fingernails to find anaemia. Such instruments would be able to measure image-based factors with great accuracy, such as pallor and the erythema index (EI). Pre-processing, segmentation, feature extraction, and classification are the fundamental sub-processes that make up the CADx method for diagnosing anaemia. [7]. The framework has the potential to be a reliable and effective way for detecting anaemia from blood smear images, which will improve medical diagnostics. The amount and diversity of the supplied dataset may have an impact on the framework's performance, necessitating thoughtful deliberation and augmentation to guarantee resilience across varied populations of patients and conditions.

The key contribution of this model is given below:

1) To increase the accuracy of anaemia detection, the WO-GCNN system combines the strength of generative models, namely Generative Adversarial Networks (GANs) and convolutional neural networks (CNNs).

2) The WO-GCNN solves the problem of insufficient data to train deep learning models by creating false blood smear images and understanding the fundamental information distribution through the use of GANs.

3) To discover the best combination of CNN weights, the approach effectively strikes an equilibrium between exploration and exploitation by incorporating the Whale Optimisation Algorithm (WOA) into the training phase of the WO-GCNN.

4) The suggested WO-GCNN method exhibits extremely precise and efficient anaemia recognition, with the potential for early identification and enhanced patient care in the area of medical imaging analysis.

5) An innovative method for overcoming the difficulties of detecting anaemia from blood smear images is demonstrated by the integration of generative models and CNNs with the WOA optimisation.

The structure of the essay is organised as follows: The associated work was covered in Section II. Section III describes the problem statement. Section IV describes the suggested convolutional Neural Network algorithm for identifying anaemia. In Section V, the proposed method's effectiveness and performance were evaluated, and the findings were shown in graphs and tables. The final Section VI provides a summary of the paper's findings.

II. Related Works

Alzubaidi et al. [8] proposed Red blood cells (erythrocytes), which are elongated, circle (normal), and other blood components, are divided into three groups using three deep learning models. The suggested models were created using classic and parallel convolutional layers, two types of convolution neural networks. The amount of layers and learnable filters in these models are different. The most effective model out of the three has been determined empirically. In this study, transfer learning and data augmentation were used to address the problem of not having enough data for training deep learning models for the classification of red blood cells. The target dataset's images were gathered from the identical domain using the comparable domain transfer learning technique, and previously learned models were then suggested and trained. The categorization task for sickle cell disease was subsequently enhanced using these previously trained models. Our models were assessed using two datasets. The experiment's findings demonstrated that classifying sickle cell disease using the identical domain transfer learning greatly increased. It also made it possible for our algorithms to work better than the most recent erythrocyte classification techniques. By reaching an accuracy of 99.54% with the framework alone, 99.98% with the approach plus a multiple classes SVM classifier on the erythrocytes DB dataset, and 98.87% on the gathered dataset, our model exceeded the most recent techniques and reached state-of-the-art performance. Last but not least, training a multiclass SVM classifier demonstrated its efficacy in extracting features and produced excellent outcomes. The drawback is that the model needs to be taught in doing the following job to be able to classify white blood diseases.

Kilicarslan et al. [9] explains The two combined models for predicting HGB-anemia, B12 deficiency anaemia, nutritional anaemia (iron deficiency anaemia and folate deficiency anaemia), and individuals without anaemia have been developed using genetic algorithms (GA) and deep learning algorithms of arranged auto encoder (SAE) and convolutional neural network (CNN). The developed GA-SAE and GACNN approaches use GA for optimising the high-level parameters of the SAE and CNN algorithms because it can be difficult to choose acceptable values for deep learning algorithms. The suggested algorithms' estimations and classification results were assessed using the accuracy, precision, F-score, and sensitivity criteria. The newly developed GA-CNN approach, whose layers were continuously trained separately of one another, was 98.50% more efficient than that of the study presented in the literature, according to the lab's evaluations utilising the dataset. The suggested combinations look at medical data to make diagnosis while lowering human error because of infirmity or exhaustion. This indicates how ineffective and unsuccessful it is.

Haematological condition sickle cell anaemia was once considered to be one of the special characteristics of the indigenous population, but it today affects everyone in the world and calls for immediate medical attention. Yeruva et al. [10] describes The history of Sickle Cell Disease (SCD), both nationally and internationally (in the context of India). the description of the disease's signs and symptoms, caution signs, effects, and treatment. Blood characteristics are also used to categorise the blood cells in individuals with sickle cell disease and thalassemia patients. This study utilises a multi-layer perceptron to better accurately simulate sickle cell disease with the goal to decrease the period and energy needed for sickle cell disease painful control systems. In this work, we investigate the "MLP Classifier" deep learning model, which outperforms methods like Support Vector Machine, Decision Tree Classifier, K-Nearest Neighbour, Random Forest Algorithms, and Logistic Regression in terms of output. According to simulation results, the proposed MLP classification has an accuracy of 99.9% for predicting both sickle cell and thalassemia. Normal medical lab workers cannot apply the MLP classification algorithm and prediction model in the TSCS scenario since it is not faster or quicker.

El-kenawy et al. [11] proposed employing haematological criteria, machine learning is being used for prediction and to approximate the market value of haemoglobin. Considering the Random Forest, Support Angle Device, and Artificial Neural Networks three computer learning techniques. The least expensive mistake was made by K.N.N. Set. In conclusion, the current investigation revealed aberrant RBCs, HGB, HCT, and CRP levels in the CBCs of frequent COVID-19 cases, which were also the most likely laboratory findings in these patients. We provide a machine learning approach in this study to estimate blood level based on bloodstream test criteria. Pre-processing is done in our suggested method for haemoglobin evaluation so that data is minimised and normalised immediately before training the models. The results of this technique are contrasted with those from different manufacturers' learning versions. A precise Blood assessment is produced by the suggested version. When reading the CBC of COVID-19 patients, clinicians should take these factors into account. To improve the highest possible accuracy new optimization algorithm is utilised.

El-kenawy et al. [12] explains classification and regression are two machine learning tasks. Using haematological data, estimating the value of haemoglobin for the regression. Three machine learning techniques, namely Random Forest, Artificial Neural Networks, and Linear Regression, were employed. The least mistake was generated using random forest. The type of anaemia is then classified using the haematological parameters and the estimated haemoglobin levels. Comparing Decision Tree against Random Forest, Artificial Neural Networks, and Naive Bayes, it became clear that Decision Tree was the superior classifier. Finally, we suggested an ensemble model (HEAC) that combines the Decision Tree classifiers, Naive Bayes, and Random Forest. The proposed model performed better than current classifiers and decision trees. Before training the models, pre-processing reduces and normalises the data in the Haemoglobin Estimation and Anaemia Classification (HEAC) method that we recommend. Results obtained from various machine learning models are compared to results from this model. The haemoglobin estimation and anaemia classification findings from the suggested method are quite precise. Genetic algorithms are used to obtain the greatest precision and identify the best weights.

Sickle cell anaemia (SCA) is a significant haematological condition which often requires hospitalisation over the course of a patient's lifetime and may even be fatal. Aliyu et al. [13] presents a two-step process Initially identify the RBC region of interest (ROI) using automatic red blood cell (RBC) extraction from a person's blood smear image. In order to categorise and forecast whether anomalies will be found in SCA patients, a deep learning AlexNet model is used. The research included (nearly 9,000 single RBC pictures) from 130 SCA patients, with 750 units for every category, with the goal to provide an overall multiscale forms assessment and shape factor quantization. We demonstrate how the suggested structure can automatically categorise 15 different RBC shape types, includes normal, using a sophisticated AlexNet transfer learning model. The specificity, sensitivity, precision and accuracy of the cell's name categorization predictions were 95.92%, 77%, 98.82%, and 90%, respectively. It requires a lot of time to perform.

III. Problem Statement

The improvement of categorization and model predictions for diverse haematological disorders, such as sickle cell disease and anaemia, is the main focus of the issue statement discussed in this study. To guarantee prompt medical attention, these illnesses must be accurately identified and classified due to their major global effects. However, a number of obstacles prevent this field from progressing. First of all, deep learning models struggle to operate at their best due to a lack of training data. Furthermore, the effectiveness and success rates of current studies are frequently low, emphasising the need for better methods. Another issue is computational time efficiency. Additionally, there are difficulties in using these models in real-world medical laboratory settings, necessitating easier and more accessible solutions. As a result, the issue statement focuses on creating reliable and accurate classification and prediction models, overcoming data constraints, enhancing effectiveness, ensuring practical use, and speeding up the diagnosis and treatment of haematological disorders [14].

IV. Proposed WO-GCNN Method for Anaemia Detection

A convolutional Neural Network is used for image collection, pre-processing, feature extraction, feature selection, and categorization in order to detect and recognise the anaemia. The collected examples of photos have been posted. In pre-processing, filtering is employed to get rid of noise, and operations are used to find the edges of the image. The relevant traits are then extracted, and the classification of normal and pathological cells are done. Fig. 1 shows the block diagram for classification of anaemia using WO-GCNN mechanism.

A. Data Collection

Consulting pathologists gathered, organised technically, and annotated blood imaging data for the suggested method. A 40x Olympus Dp27 lens was used to examine the blood smear slides. Images at a resolution of 1920 x 1080 pixels were taken with an 8.9-megapixel CMOS sensor. From 50 blood smear slides, it has 500 images in total, 250 of which are healthy and 250 of which are anaemic RBC images. Those without anaemia are represented in the images, while those with anaemia are represented in the images [15].

The dataset is partitioned into three separate sets or folds for 3-fold cross-validation. The remaining two folds are utilised for training, while each fold is used once as a validation set. To guarantee every subset has been utilised as a validation set precisely once, this procedure is repeated three times. The total number of photos and the proportion of normal and anaemic red blood cells (RBC) images in each fold are displayed in the Table I.

TABLE I. 3 Fold Cross Validation of Healthy and Anaemic RBC Images

Folds	Total images	Healthy RBC images	Anaemic RBC images
1	167	83	84
2	167	83	84
3	166	84	82

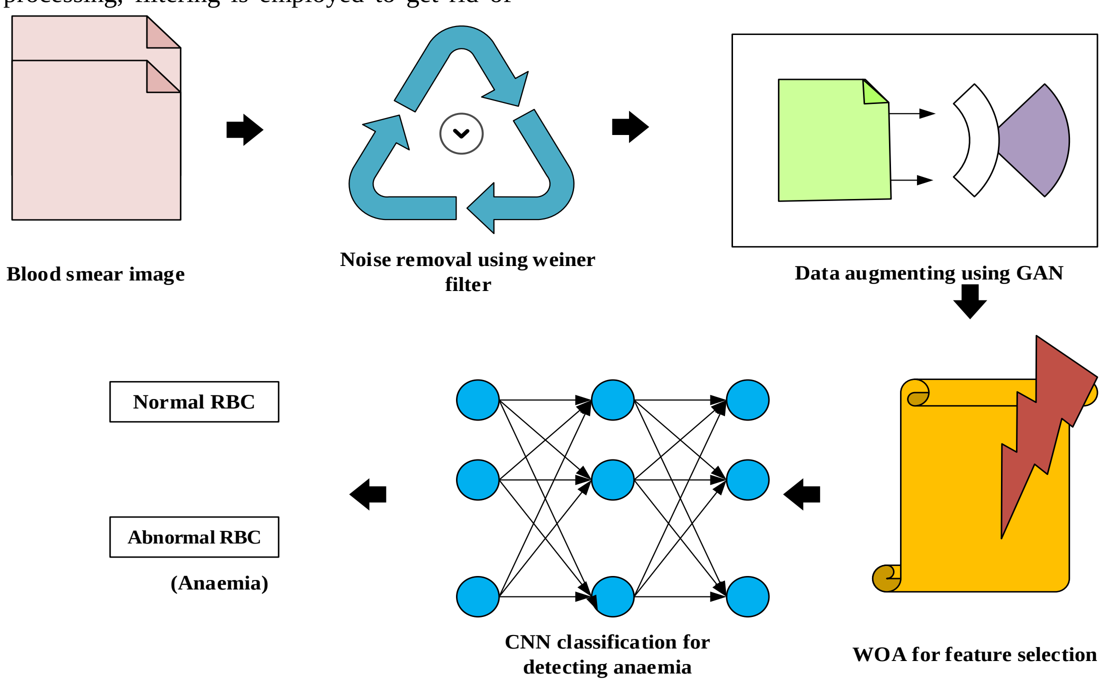

Fig. 1. Classification process of anaemia.

B. Data Generation using GAN

The generative models known as GANs are built on adversarial and deep learning techniques. GANs' main objective is to learn and replicate the distribution and traits of some interesting data in order to create similar data of the same type. A discriminator and a generator are the two neural network models that make up GANs. The discriminator is taught to categorise the veracity of the data it receives as input. The generator is adept at creating new artificial information that is exact replicas of the real information. Although the discriminator and generator systems are trained concurrently, they have various goal (as well as loss) parameters [16].

The discriminator's goal is to increase the probability that it can tell the difference between genuine data (from the training set) and fictitious data from the generators. For labelled genuine training data x, log (D_0(x)), D_0 (x) is ideally 1, and for fake data z produced by the generatorG_0, its loss is log (1 – D_0 (G_0 (z))). Loss is measured using cross-entropy. The discriminator's aim for identifying authentic and fraudulent data is then maximised during training using feedback from its loss measurement loop is given by eq. (1).

$$\max_{D_0} V_0(D_0) = E_{0_{x\sim P_{data}(x)}}[logD_0(x)] + E_{0_{z\sim P_z(z)}}[\log\left(1 - D_0\left(G_0(z)\right)\right)] \quad (1)$$

Another reverse propagation feedback process from the discriminator drives training of the generator with the goal of reducing the likelihood that the generator's bogus data will be identified in eq. (2).

$$\min_{G_0} V_0(G_0) = E_{0_{z\sim P_z(z)}}[\log\left(1 - D_0\left(G_0(z)\right)\right)] \quad (2)$$

Equation (3) contains the whole GAN objective function.

$$\min_{G_0}\max_{D_0} V_0(D_0, G_0) = E_{0_{x\sim P_{data}(x)}}[logD_0(x)] + E_{0_{z\sim P_z(z)}}[\log\left(1 - D_0\left(G_0(z)\right)\right)] \quad (3)$$

The discriminant and generation compete during GAN training in a manner comparable to a zero-sum mini-max game. Training proceeds till the GAN structure combines, at which point (i) the discriminator is able to distinguish between genuine and phoney data with adequate accuracy and (ii) the generator produces data that the discriminator has an extremely small likelihood of finding. The GAN network needs to be retrained if just one of the two results is (i) or (ii) [16].

C. Pre-processing

The augmented anaemia dataset is used in pre-processing for removing the extra noises. An image of the binary model of the multi-coloured blood stain is created. The picture is then improved. The Weiner filter is a flexible noise reduction device. A clearer picture of the concentration, in this case just the red blood cells in the blood sample, is then provided by clearing up the picture. The acquired image is then put to use in additional processing. In the pre-processing stage, noise reduction, unwanted effects like noise are reduced or eliminated with the goal of preparing the image for subsequent processing. Wiener equation is calculated as eq. (4)

$$W = (F^{-1}x)^2 \quad (4)$$

The following equation can be used to calculate the gradient is shown in eq. (5,6)

$$g_0(m, n) = G_{0_\sigma}(m, n) * f_0(m, n) \quad (5)$$

$$\text{Where, } G_{0_\sigma} = \frac{1}{\sqrt{2\pi\sigma_0^2}}\exp(-\frac{m^2+n^2}{2\sigma_0^2}) \quad (6)$$

Using any gradients operator [17], such as Roberts, Prewitt, Sobel, or another method, the gradient of $g_0(m, n)$ is calculated to obtain in eq. (7)

$$M_0(n, n) = \sqrt{g_{0_m}^2(m, n) + g_{0_n}^2(m, n)} \quad (7)$$

D. Sobel Operator for Edge Detection

Edge detection is a technique for spotting breaks in images. Edge detectors come in a variety of varieties, including Sobel Operator, LoG Operator, Robert's Operator, and Zero cross Operator, Canny Operator, and Prewitt Operator. The Sobel Technique is presented below among all of these. It serves as an edge detector with 33 gradients. The Sobel algorithm calculates the 2-D spatial gradient of a picture and highlights edge-corresponding regions with higher spatially frequency. When a grayscale image is provided, it is utilised to determine the roughly absolute magnitude of the gradient at each location. The Sobel Operator uses 2 3×3 matrix that are convolved with the starting image, one for horizontally variations and one for vertically shifts, for approximating the derivatives of the image. The Sobel operator may be utilised to calculate the predicted relative magnitude of gradients at each position of a given grey scale image by applying 2-D spatial gradient measurements on the image and emphasising regions of high spatial frequency that correspond to edges. Therefore, the Sobel operator is used in the edge identification of biomedical images [18].

E. Whale Optimization Algorithm

Mirjalili and Lewis developed the whale optimisation algorithm (WOA), a new metaheuristic technique. The global optimum answer for an issue is sought after and discovered using WOA, which works similarly as various metaheuristic optimisation methods. Update until the optimal value is attained, the algorithm keeps enhancing and updating the answer depending on its framework. The way the WOA principles update and refine the answer is the main distinction between the WOA and other metaheuristic algorithms. The WOA is modelled after the instinctual way that whales hunt prey—by spiralling around it to set up a trap and then hitting it. This type of eating behaviour is known as bubble-net feeding [19].

Before striking, the humpback whale spirals around its prey to produce bubbles. This consuming behaviour served as the basis for the WOA's primary structure. The bubble-net method's mathematical framework is described as follows in eq. (8) to (10).

$$X_0(t+1) = \begin{cases} X_0^*(t) - AD & P < 0.5 \\ \acute{D}_0 e_0^{bl} \cos(2\pi t) + X_0^*(t) & P \geq 0.5 \end{cases} \quad (8)$$

$$\acute{D}_0 = |CX_0^*(t) - X_0(t)| \quad (9)$$

$$A = 2ar_0 - a \quad (10)$$

$$C = 2r_0 \quad (11)$$

Where, $\acute{D}_0$ → Distance between the ith whale and its victim (the ideal answer), P and r_0 → random constants between 0 and 1, l → a random constant between [1, 1], t →current iteration, b → the logarithmic spiral's form, and a → linearly across the iteration, from 2 to 0.

The circling process is represented by the initial term in the formula above, while the bubble net process is represented by the following term. The extraction and utilisation terms of the WOA are represented by these two clauses. It shows how the prey is circled and how bubble-net hunting is done. The WOA begins with a randomly chosen populace, as was already mentioned. The results are then updated after every round in accordance with the mathematical model created for hunting using a bubble net and orbiting the prey. When $|X_0|$> 1, the optimum solution adjusts the location of the agents to ensure that the algorithm converges. If not, the most effective solution serves as a pivot point.

Algorithm of WO-GCNN mechanism for detecting anaemia

Start
Input: Initializing the whale population X_{0_i}
Initializing a, A_0, and C
Output: Evaluating the most effective solution is displayed by search agents with fitness X_0 at this time.*
Applying WOA: for feature selection
t_0=1
while doing t_0<max iterations
for the agents do in all
if $|A_0|$=1 then
Updating the search's current location
Else if $|A_0|$=1 then
Choose the $X_{0_{rand}}$ random search agent.
Updated the current agent position
End if
End for
Updating a, A_0, and C
Updating X_0^*
t_0= t_0+1
End while
return X_0^*
End

The computational difficulty of WOA is O_0 (Max Gen NP O_0 (fitness)), where Max Gen is the maximum number of generations and O_0 (fitness) is set by the application. This is because WOA has a fairly basic structure, based to the pseudocode [19].

F. Convolutional Neural Network

A set of layers collectively referred to as CNN are used for converting the input layer into an output layer. Each layer is made up of a collection of neurons. Each neuron in a layer, with the exception of the input layer, is the outcome of the task that was assigned to the neurons in the layer before it, i.e. y=f(x). The most often used layers are the convolutional layer, the fully connected layer, the pooling layer, and the activation layer, Fig. 2.

Each neuron in a layer that is fully connected is connected to all of the neurons in the layer below it. The strength of the connection connecting the jth neuron in the current layer and the kth neuron in the previous layer should be represented by the number$\omega_{0_{jk}}$. Let b_{0_j} be the bias of the jth neuron in the current layer. The result of the layer's jth neuron is given by eq. (12)

$$y_{0_j} = \sum_k \omega_{0_{jk}} x_{0_k} + b_{0_j} \quad (12)$$

The neurons in the convolutional layer that are typically used for generating a kernel or filter have identical biases and values. Each neuron in this layer will be connected to a n×n region of the neurons in the layer beyond if the size of the filter is set to n×n. In line with this, the (j, k) th neuron's outputs will be in eq. (13)

$$y_{0_{j,k}} = \sum_{l=0}^{n-1} \sum_{m=0}^{n-1} \omega_{0_{l,m}} x_{0_{j+l,k+m}} + b \quad (13)$$

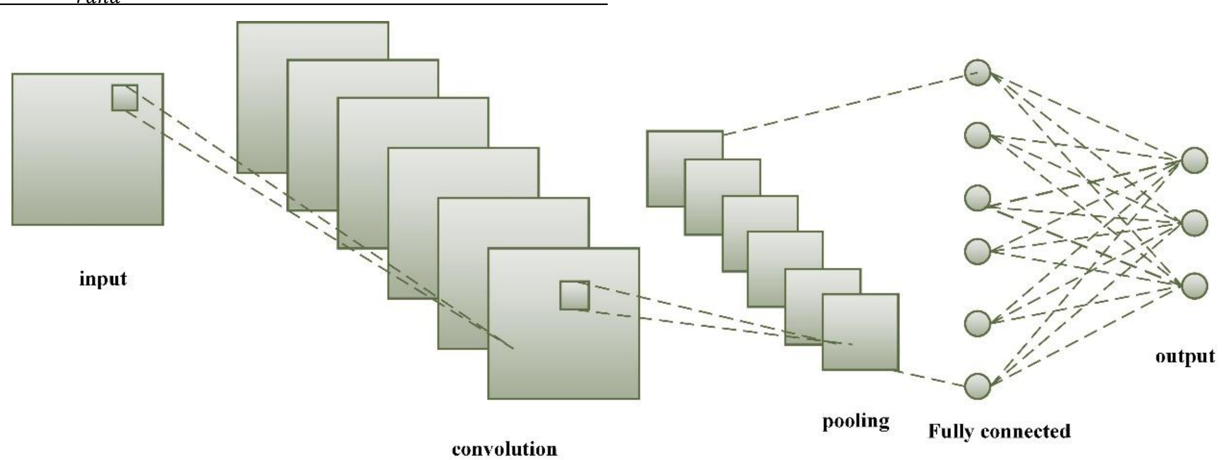

Fig. 2. Convolutional neural network architecture.

Tanh, Sigmoid, and the rectified linear unit, that has become the standard suggestion for modern neural networks, are instances of frequently employed functions for activation. Activation layers usually appear following convolutional or fully connected layers to offer elementwise non-linear behaviour. By using the activation function, ReLU is defined in eq. (14)

$$f_0(x) = \max(x, 0) \tag{14}$$

The downwards sampling method for every sub-area in the pooling layer provides the dimension of a single neuron in the present one by dividing the neurons of the layer preceding it into an array of not overlapping rectangles. Maximum pooling and average-pooling, the two most popular pooling procedures, offer the subarea's maximum value and average value, respectively [20]. A convolutional neural network usually sets up a sequence of convolutional (Conv)-ReLU layers, before adding the pooling layers (Pool), and continues doing this till the picture gets spatially combined to a compact size. At certain points, it is usual to switch to fully-connected layers (FC).

V. Results and Discussion

A normal blood sample is pre-processed, binarized, and the permeability of each connected component is determined using MATLAB 7.14.0.739 software. Similarly, an anaemic blood specimen is binarized, pre-processed, and the permeability of each associated component is determined.

A. Performance Evaluation

The classification methods' performance was evaluated using the confusion matrix's assessment measures (Table II). Although the true negative (TN) represented the conjunctiva images that the machine learning algorithm accurately identified as not considered anaemic, the true positive (TP) represented the conjunction tissue images that the classification successfully classified as being in the anaemic class. False positives (FPs) were conjunct images of people who were not anaemic but who were wrongly classed as being anaemic. Finally, false negatives (FNs) were found in the conjunctival pictures of anaemic individuals who were mistakenly classified as no anaemic. Accuracy, sensitivity, and specificity are defined in accordance with these notations is given by eq. (15-17).

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \tag{15}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{16}$$

$$Specificity = \frac{TN}{FP+TN} \tag{17}$$

These metrics were calculated based on every cross-validation operation that was performed, and the effectiveness of the classifier was assessed using the mean and standard deviation of the outcomes. Although the accuracy measure is typically an accurate measure of a system's effectiveness, the dataset's imbalance between the two groups makes it less reliable [21]. Since the goal of an approach like the one suggested in this research is initially aimed at giving a patient who was not aware of being deficient in iron for carrying out further examinations, it was chosen to prioritise sensitivity, which says, as a percentages, the number of the actual anaemic individuals were identified by the system.

A graph called the receiver operating characteristic curve shows the way a classification system works at every level of categorization. The curve shows the following two variables: 100% True Positive. False Positive Rate. Fig. 4 shows the ROC Curve along with the false positive rate and true positive rate. To assess the ability to discriminate of each metric in identifying anaemia, ROC curves were generated [24].

TABLE II. COMPARISON OF PERFORMANCE EVALUATION FOR PROPOSED METHOD AND EXISTING METHODS [22]

Classifiers	Accuracy	Sensitivity	Specificity
KNN	67.4%	67%	84%
SVM	78%	71%	85%
NN	79.8%	65%	91%
Proposed WOG-CNN	99%	92%	96%

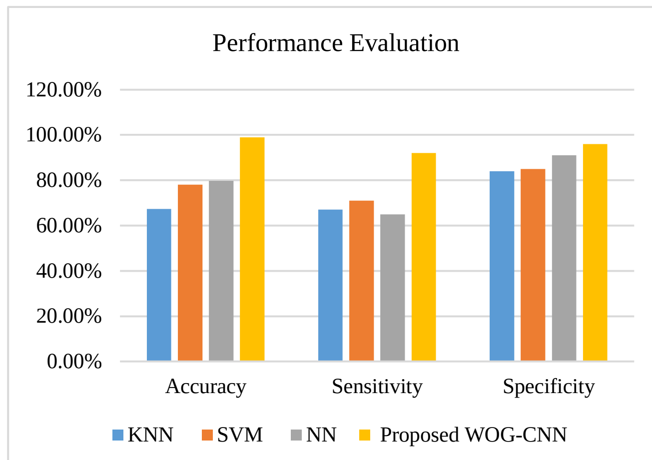

Fig. 3. Graphical representation of performance metrics.

The above graph (Fig. 3) shows that the accuracy, specificity and sensitivity of the existing and proposed model and ROC curve for false positive rate and true positive rate. This shows that the proposed method gives better efficiency.

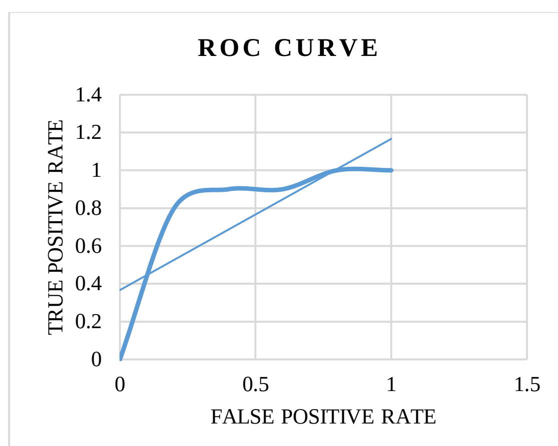

Fig. 4. Graphical representation of ROC curve.

B. Dataset Comparison

In Table III and Fig. 5, the performance of the proposed WOG-CNN model in comparison to the approach presented is evaluated using two datasets: the IDB Dataset and the Image net Dataset. The evaluation metrics used are sensitivity, accuracy, and specificity. The proposed WOG-CNN model consistently achieves higher specificity, accuracy, and sensitivity on both the IDB Dataset and the Image net Dataset compared to the approach.

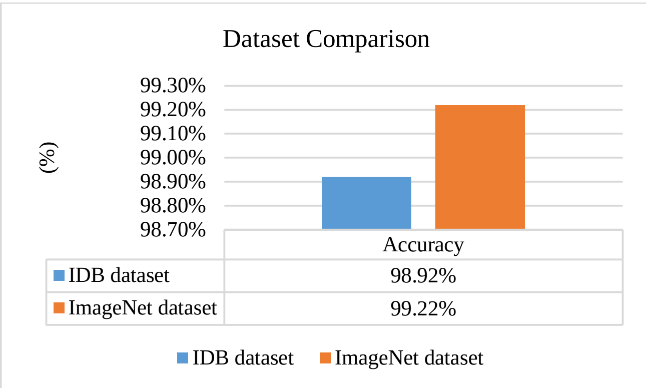

Fig. 5. Dataset comparison.

TABLE III. DATASET COMPARISON IDB AND IMAGE NET DATASET OF CNN

Datasets	Accuracy
IDB dataset [25]	98.92%
ImageNet dataset [26]	99.22%

The suggested WOG-CNN and SVM were two separate methods that were compared in this study for how well they performed on the IDB Dataset and ImageNet Dataset. On the IDB Dataset, the SVM approach produced results with an accuracy of 98.87%, a sensitivity of 91.65%, and a specificity of 91.46%. On the ImageNet Dataset, the results were even better with an accuracy of 99.54%, a sensitivity of 80.00%, and a specificity of 90.91%. The suggested WOG-CNN, however, performed better than SVM on both datasets, obtaining 99% accuracy on the IDB Dataset and 92% and 96% sensitivity and specificity, respectively. Additionally, the WOG-CNN attained an accuracy of 99.63% on the ImageNet Dataset, with a sensitivity of 87.1% and a specificity of 93.8%. These findings show that the suggested WOG-CNN outperforms the state-of-the-art in both datasets, underscoring its promise as a highly precise and reliable solution for the classification of images tasks, especially in the setting of anaemia diagnosis and beyond.

VI. CONCLUSION

This framework effectively recognises and categorises anaemia-related patterns and abnormalities in the blood smear images by combining the strength of generative algorithms and convolutional neural networks (CNNs). By optimising its parameters and accelerating its convergence, the Whale Optimisation Algorithm (WOA) is used in the framework to improve the CNN's performance. WOA is a metaheuristic algorithm inspired by nature that simulates the behaviour of humpback whales during hunting, making it appropriate for CNN optimisation. The WOGCNN framework's capacity to generate realistic synthetic blood smear images through learning helps it expand the training dataset and solve the issue of scarce data availability. This augmentation method enhances the CNN model's resilience and generalisation, enabling it to precisely identify anaemia in hidden blood smear images. The WOGCNN architecture has showed higher performance compared to conventional anaemia detection techniques through comprehensive trials and evaluations. It performs with excellent precision, sensitivity, and specificity in identifying different anaemia types and severity levels, making it an important tool for early diagnosis and treatment. This paradigm can aid in improving patient outcomes and lessening the strain on healthcare systems by enabling early detection and intervention. It is crucial to remember that additional analysis and validation are required in order to properly prove the efficacy and dependability of the WOGCNN architecture. To evaluate its effectiveness in real-world situations and guarantee its generalizability across various populations and locations, extensive clinical trials and validation on a variety of datasets are required. The proposed framework demonstrates highly accurate anaemia detection from blood smear images while achieving faster computational time.

The performance and utility of the WOG-CNN may be further improved by additional research and development in this field. The robustness and generalizability of the model could be improved by enlarging the dataset to include a wider range of samples from various populations. The accuracy and interpretability of the model may also be improved by investigating the incorporation of domain-specific information or expert annotations. The application of the WOG-CNN in actual clinical settings necessitates careful consideration of data privacy and regulatory compliance. Gaining the trust and approval of medical organisations and practitioners will depend on following ethical standards and making sure patient data is secure.

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