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Research Article

Artificial Intelligence Models for Predicting Iron Deficiency Anemia and Iron Serum Level based on Accessible Laboratory Data

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ABSTRACT

Background: One of the most important strategies for treating anaemia is early detection and therapeutic intervention to avoid irreversible organ damage. The aim of this study is to demonstrate artificial intelligence models for predicting iron deficiency anaemia and iron serum levels using available laboratory data.

Methodology: Three AI models, Naïve Bayes, Support vector machine (SVM) and Convolutional neural network (CNN) were developed to detect anaemia in captured and processed images (datasets).

Results: The CNN achieved the highest accuracy of 90.27%, while SVM had the lowest accuracy at 64.66%. Naïve Bayes achieved 89.96% accuracy.This demonstrates that data mining software is efficient and effective at detecting diseases such as iron deficiency anaemia and deficiency of iron serum levels.

Our findings illustrated that, using machine learning and explainable AI to detect anaemic conditions in blood has the potential to improve patient outcomes and benefit the healthcare industry. After being trained, validated, and tested on the datasets, the proposed models produced a significant outcome. This demonstrates that data mining software is efficient and effective at detecting diseases such as iron deficiency anaemia and deficiency of iron serum levels.

Conclusions: By creating a predictive AI model that shows promise for improving diagnostic precision and clinical decision-making in anaemia management. By leveraging data-driven approaches and advanced computational tools, healthcare systems can improve patient care, lower healthcare costs, and improve overall public health outcomes. Our study demonstrated that the use of non-invasive approaches, such as machine learning algorithms, is effective, less costly, takes less time, and produces excellent results for anaemia detection.

Keywords: AI models, iron deficiency anemia, iron serum level, predicting anemia by AI, machine learning for detecting anemia.

1. Introduction

Iron is an essential biological element that is tightly controlled at the cellular and systemic levels to prevent both deficiency and excess. Iron homeostasis, also known as the iron economy, is primarily maintained through reabsorption processes [Camaschella et al., 2020, pp. 260-272]. The recycling of red blood cells provides the majority of the body's iron—about 20-25 mg per day. In contrast, the gut absorbs only 1-2 mg of new iron per day to compensate for what is excreted. Disruptions in iron haemostasis can cause a variety of conditions, including iron deficiency, which can be caused by increased iron demand, insufficient external supply, and increased blood loss [Pierre et al., 2023, pp. 3-4]. One of the most important strategies for treating anaemia is early detection and therapeutic intervention to avoid irreversible organ damage. Symptoms include fatigue, disorientation, drowsiness, and weakness. Patients with chronic illnesses may develop anaemia [Tamir et al., 2017, pp. 697–701]. Furthermore, anaemia has been shown to reduce adult productivity, influence children's psychological and physical development, and, if left untreated, lead to health problems such as extreme fatigue and pregnancy complications. [Pasricha et al., 2021; pp. 233–248.]

Haemoglobin, a protein found in red blood cells, is essential for the transport and storage of oxygen throughout the body. It has been reported to have the ability to maintain its elasticity, spherical shape, and stability in healthy individuals. There are numerous types of anaemia, such as iron deficiency, sickle cell disease, thalassaemia, aplastic anaemia, and vitamin or iron deficiency. Every type of anaemia has a wide range of causes, which can be temporary or chronic, mild or severe.[Zopfs, et al., 2020, pp. 4350–4357]. Anaemia is usually diagnosed based on the concentration of haemoglobin in the blood, also known as the haematocrit, which is the ratio of the number of red blood cells to the total volume of a blood sample. [Islam et al., 2022 pp.118–133]

Anaemia is diagnosed when haemoglobin or haematocrit levels fall more than two standard deviations below the normal range. Meanwhile, haemoglobin and haematocrit levels in the blood may not accurately reflect the severity of anaemia in a patient with a low RBC mass who is also suffering from hypovolemia-caused dehydration-induced plasma volume loss because the values are likely to be within the normal range.[Holzinger et al., 2019, pp. 1312]. Artificial intelligence (AI) is defined as the attempt of computers to mimic human cognitive processes.[Briganti et al., 2020 pp. 27]. AI programming emphasises three cognitive skills: learning, reasoning, and self-correction. This aspect of AI programming entails collecting data and developing rules to convert it into actionable knowledge.[Dana, et al., 2022, pp. 509-522].

Modern information technology and computational advancements, such as artificial intelligence (AI), offer unprecedented opportunities to process large amounts of diverse data and gain a better understanding of iron homeostasis. This may allow clinicians to make more informed decisions about the best treatment options for people with iron excess or deficiency.[Abujaber, et al., 2022, p. 101090].

AI could enhance the use of big data to achieve personalised or precision medicine. For example, using image recognition capabilities, machine learning (ML) methods, a subset of AI, can help identify specific histological aspects of chronic conditions like chronic liver disease. Although the use of AI in medical research and practice is still in its infancy when compared to other industries, AI-based imaging offers novel options for predicting prognosis and complications, with the ultimate goal of precision/personalised medicine.[Dithy et al., 2019, pp. 2623–30]. The aim of this study is to demonstrate artificial intelligence models for predicting iron deficiency anaemia and iron serum levels using available laboratory data.

2. Literature Review

Non-invasive approaches, such as the use of machine learning algorithms, are among the procedures and methods used in detecting clinical diseases, and anaemia detection is no exception in recent times. [Mazzu-Nascimento et al., 2021 pp. 55-60]. Regarding the invasive method of detecting anaemia, which is costly, time-consuming, and painful for patients due to blood extraction, and which occasionally exposes clinicians to pricking the cause of the blood extraction.[Karagül 2021, pp. 50–70] In comparison to the invasive method, the non-invasive approach is less expensive, takes less time, and is more reliable because it uses the palm, conjunctiva, tongue, and fingernails. While these human features can be used to detect anaemia by assessing their paleness by medical officers, this is mostly up to the discretion of the physician or health official.[Pasricha et al., 2021,pp. 233-248]. Anaemia can also be confirmed or detected by measuring the amount of haemoglobin in the blood, also known as the haematocrit, which is the ratio of red blood cells to total blood volume. Anaemia is defined as having haemoglobin or haematocrit levels that are more than two standard deviations below normal.[Saputra et al., 2023, p. 697].

Anaemia can also occur when the Hb level in red blood cells falls below the normal threshold, which is caused by one or more of the following: increased red cell destruction, blood loss, defective cell production, or a depleted red blood cell count. [Karagül et al., 2021, pp. 50-70]. Early detection of anaemia symptoms is an ideal primary stage for alleviation because if anaemia is not detected and treated in a timely manner, it irreversibly damages the human organ, potentially leading to death.[Appiahene et al., 2023, p. 2]. Iron deficiency anaemia has also been shown to have an impact on children's psychological and physical development, as well as reduced adult productivity. Long-term illness can also increase a patient's risk of being diagnosed with anaemia. Diabetes, kidney syndrome, cancer, human immunodeficiency virus, inflammatory bowel disease, and cardiovascular disease are all syndromes associated with a high prevalence of anaemia.[El-kenawy et al., 2019,pp. 100–108].

Several studies have been published on the use of machine learning to categorise various types of anaemia, including one that predicted data in the form of a complete blood count (CBC) and built a model to detect anaemia.[Khan et al., 2019, pp. 195-218 and Xiaoyan et al., 2023]. Machine learning for medical care has advanced dramatically over the last century, particularly in the forecasting of anaemia, which has piqued many people's interest. Recently, researchers have used machine learning methods to deeply analyse and predict anaemia, making significant progress. [Asare et al., 2023].

Machine learning can be used to solve a wide range of problems, including discovering relationships between two variables, classifying concepts using unique standards, predicting with initial features, and identifying similar patterns in items. In terms of anaemia prediction, machine learning has already been widely used to analyse various anemia-related causes. [Delgado-Rivera et al., 2018, pp. 1- 4]. For example, patients' ages, genders, and dietary habits. Additionally, popular machine learning methods are used for anaemia forecasting. Furthermore, popular machine learning methods, such as k-Nearest Neighbour (k-NN) and Convolutional Neural Networks (CNN), are included for forecasting anaemia. [Shahzad et al., 2022, p.5030]. According to a World Health Organisation study, 42% of children under the age of six and 40% of pregnant women worldwide are anaemic. Anaemia affects 33% of the global population due to iron deficiency. Anaemia occurs when the body's red blood cell count decreases or when the red blood cell structure is destroyed or weakened.[Irum et al., 2016]

Using 19 conjunctivae images from the eye, an SVM approach was used to computerise a non-invasive model for detecting anaemia. The images corresponded to the various haemoglobin levels known, with an accuracy of 78.90% in 15 of the 19 cases. Irum et al. used the least squares support vector machine (LS-SVM) to detect anaemia in conjunctiva images of the eyes, combining image processing and computer vision. The procedure yielded 85% precision, 92% sensitivity, and 70% specificity. The study examined 77 tested images, 21 of which were non-anemic and 56 of which were anaemic.[Jain et al., 2019]. Ghosh et al. estimated Hb levels using ANN and biodata, extracted blood samples, and images from 86 patients. The colour intensity of the extracted blood images was calculated using the sample feature descriptions. [Ghosh et al., 2023] When the features were extracted from the collected dataset and fed into the proposed ANN model, the study achieved a sensitivity of 95.50% and a specificity of 52%. [Hortinela et al., 2019].

A study found that an SVM classifier was 93.33% accurate in detecting several types of RBC, including normal, echinocytes, dacrocytes, elliptocytes, spherocytes, stomatocytes, target cells, and unknown cells. They suggest that the SVM algorithm could help with the diagnosis of some conditions, such as iron deficiency anaemia, hereditary spherocytosis, myelophthisic anaemia, and thalassaemia. [Shahzad et al., 2022] Another study used a three-tier CNN-based model (3-TierDCFNet) to evaluate peripheral blood smears of 50 people, half of whom were anaemic, to detect anaemia. The deep learning system was able to first classify patients as healthy or anaemic, and then analyse the size, shape, and central pallor size of RBCs to determine the severity of anaemia. As a result, the proposed AI model had an accuracy of 91.37 in training, 88.85 in validation, and 86.06% in testing.[El-kenawy et al., 2019]

In a study, researchers used machine learning models to evaluate blood test results in two ways: regression and classification. In regression, Al systems should estimate the value of haemoglobin using other blood parameters such as RBC and WBC counts, MCV, MCH, and MCHC levels. By comparing three AI algorithms, they discovered that Random Forest produced the fewest errors when compared to Linear Regression and ANN. Classification algorithms combine all parameters in blood tests, including haemoglobin values, to classify the anaemia type. Decision Tree outperformed Random Forest, Naïve Bayes, and ANN. Combining Random Forest, Naïve Bayes, and Decision Tree resulted in a more accurate hybrid machine learning system compared to the individual algorithms [Erol Terzi et al., 2024].

In a recent study, the accuracy of statistical results was tested using the Machine Learning Method (MLM) while investigating the factors influencing the correct diagnosis of Iron Deficiency Anaemia (IDA). The results from both stages were compared. As a result, haemoglobin (Hb), mean cell volume (MCV), iron (Fe), and ferritin (FERR) have been shown to have a greater effect on IDA. ANN (98.06%) is a more effective discriminator, with a higher classification accuracy.[Alemu et al., 2024]. In a study, multiple machine learning algorithms were used to determine the most effective model for predicting anaemia in young Ethiopian girls. The model's performance was evaluated using evaluation metrics in Python software. Several data balancing techniques were employed, and the Boruta algorithm was used to select the most relevant features. Furthermore, association rule mining was carried out using the Apriori algorithm in R software. Among the tested classifiers, the random forest classifier outperformed the others in predicting anaemia, with an AUC value of 82%. [Mehmet et al., 2023]

A previous study found that rule-based machine learning algorithms could provide a new approach to risk factors for iron deficiency anaemia during pregnancy. This model can be used to predict the risk of anaemia before and during pregnancy, allowing preventative measures to be taken. The Jrip, OneR, and PART algorithms estimated factors associated with anaemia with 96.36%, 85.45%, and 97.98% accuracy, respectively. [Peter et al., 2023]. A recent study found that the Naïve Bayes and CNN models performed well in detecting anaemia using the palm. The Naïve Bayes achieved 99.96% accuracy, while the SVM had the lowest accuracy at 96.34%.[Mazen et al., 2024]

The comparative analysis study used various AI algorithms, including Convolutional Neural Networks, Support Vector Machines, Decision Trees, k-Nearest Neighbour, Naïve Bayes, Logistic Regression, Random Forest, AlexNet, ELM, XGBOOST, LGMBoost, RESNet-50, MobileNet20, EfficientNet-B3, Dense Net 121, CNN Allnet, and ANN. The hand palm is the most reliable body region for anaemia detection, and the Naïve Bayes algorithm has the highest diagnosing accuracy at 99.96%. This narrative review demonstrates that using non-invasive methods for detecting and diagnosing anaemia may provide a reliable alternative for quick, low-cost anaemia screening, particularly in non-clinical and low-resource countries.[Elmaleeh et al., 2024]

A recent study compares these classifiers to established models like the Feed Forward Neural Network (FFNN), Elman network, and Non-linear Auto-Regressive Exogenous model (NARX). Experimental evaluations were carried out on 230 patients' clinical laboratory test results. The proposed neural network has nine inputs (age, gender, RBC, HGB, HCT, MCV, MCH, MCHC, and WBCs) and one output. The simulation results for a variety of patients show that the proposed artificial neural network detects the disease quickly and accurately.[Ferih et al., 2023]. A recent study found that to diagnose thalassaemia, various indices and algorithms are used based on complete blood count (CBC) parameters. In this article, we will look at how effective artificial intelligence is at diagnosing and classifying thalassaemia.[Appiahene et al., 2023].

3. Methodology

We generated a specific protocol to collect patient information, focussing on demographic variables such as age (which for this study was limited to 18 to 25 years) and gender of the participants. We also included a list of symptoms associated with iron deficiency anaemia that participants had reported experiencing in the previous month, such as fatigue, weakness, palpitations, dyspnoea (shortness of breath), dizziness or lightheadedness, angina (chest pain), cold extremities, and cephalalgia.

Laboratory reports for anaemic adult patients (Hb <7.5 mmol/L for females and <8.5 mmol/L for males) were selected based on a complete blood count and Iron serum levels (Ferritin, Transferrin, and Total iron binding capacity level). To detect anaemia using AI models, the dataset must go through three phases or steps.

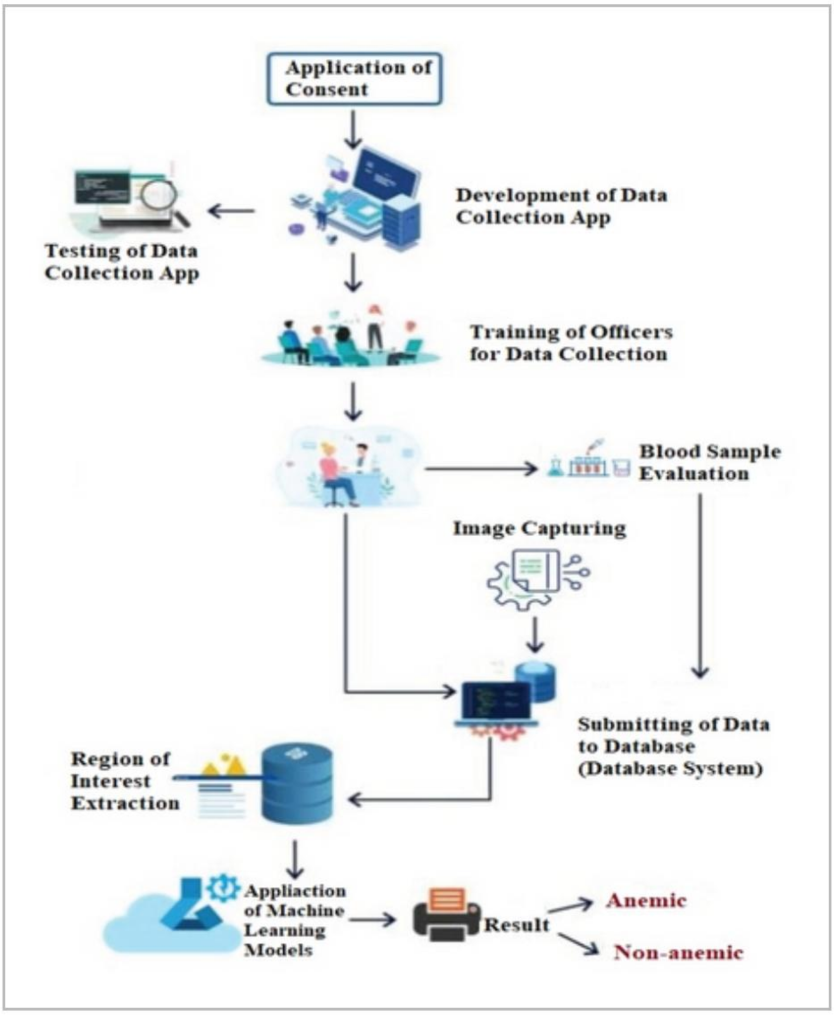

Figure (1): Illustrates the conceptual framework used.

Stage I: Image capture (dataset collection) the conjunctiva of the eyes, palpable palm, and fingernails) photographing palpable palms, conjunctivae of the eyes, and fingernails. Stage II: Image preprocessing and ROI extraction. Following that, we separated the images' CIE L*a*b* (also known as CIELAB) colour space components, segmented them, and calculated the mean intensity of the various CIE L*a*b* colour space components (ROI extraction and segmentation). Stage III: Create detective (anaemic or non-anemic) models. Machine learning algorithms (Naïve Bayes, CNN, SVM) were developed to detect anaemia in captured and processed images (datasets).

3.1 AI models used for the study:

3.1.1 Naïve Bayes:

The Naïve Bayes classifier predicts a class or category using probability based on a given set of features. It is referred to as a probabilistic classifier due to its strong independence assumptions based on probability models. [Peksi et al., 2021, p. 118] Because there are no hyperparameters to adjust, Nave Bayes usually generalises well.[Noor et al., 2019, pp. 24-28].

3.1.2 Support vector machine (SVM):

SVMs are a relatively new and popular class of classification tools that combine elements of previous methods. SVMs, like discriminant analysis, begin with the assumption that the data are "separable," meaning that they can be divided into groups using a functional separator.[Aneja et al., 2021].

3.1.3 Convolutional neural network:

CNN uses filters to identify image features multiple times in order to categorise objects. The CNN has a kernel edge that highlights pixels based on differential values of large pixels, as these features are extracted using the CNN scheme responsible for the kernel. The CNN was trained with AlexNet, SGD optimisation, and ReLu. The activation function uses a regularisation of a = 0.0001 with a maximum iteration of 10. The activation function's primary function is to convert the nodes' signal inputs to signal outputs. Without the activation function, the CNN would devolve into a linear regression, making it incapable of training complex models.[Tharwat, 2021, pp. 168–192].

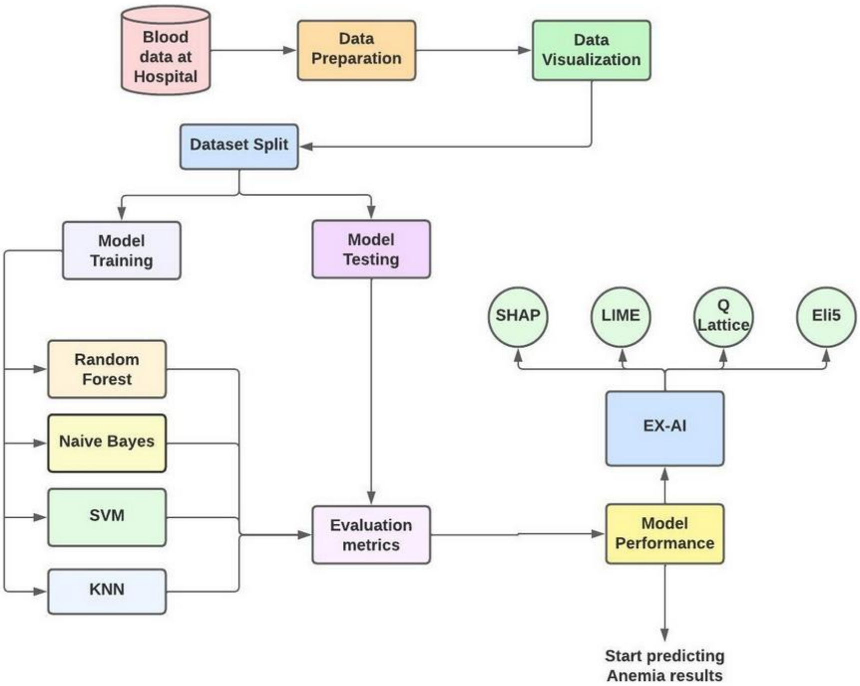

Figure (2):The process flow of classification of anemia.

To prepare the dataset for model training, several data preparation techniques were used, including data scaling and mutual information analysis. Mutual information analysis was used to identify the most relevant characteristics for predicting haemoglobin anaemia. To evaluate the model's performance and ensure its robustness and generalisability, the dataset was split into training and testing sets.

4. Results and Discussion

Our findings illustrated that, using machine learning and explainable AI to detect anaemic conditions in blood has the potential to improve patient outcomes and benefit the healthcare industry. After being trained, validated, and tested on the datasets, the proposed models produced a significant outcome. The CNN achieved the highest accuracy of 90.27%, while SVM had the lowest accuracy at 64.66%. Naïve Bayes achieved 89.96% accuracy on the dataset. This demonstrates that data mining software is efficient and effective at detecting diseases such as iron deficiency anaemia and deficiency of iron serum levels.

However, Emmanuel et al. used a CNN approach to detect anaemia and achieved an accuracy of 89.33%.[Folorunso et al., 2021, pp. 35–49].

Table (1): Comparison of other related works results.

References	Proposed technique	Algorithm used	Accuracy achieved
Dada et al.[30]	Classification supervised learning	CNN	89.3%
Peksi et al.[31]	Classification supervised learning	Naïve Bayes	90%

Noor et al.[28]	Classification supervised learning	SVM	60%

The clinical approaches used to detect anaemia rely on blood extraction, which requires more labour and instrumentation costs, as well as being a time-consuming technique that exposes health workers to blood-transmissible diseases. The proposed models' effectiveness and efficiency would have a significant impact on health facilities in terms of detecting iron deficiency anemia. The datasets used Hb values: <11 g/dL indicates anaemia and >=11 g/dL indicates non-anemia. Image augmentation techniques are used to perform procedural operations on artificially generated images, such as rotation, shift, flip, translation, and so on. Anaemia data is difficult to come by.

Rotation: During image augmentation, the actual image is rotated 90° and 270° to obtain the artificial image, with the mean intensity values remaining constant as the images' positioning varies. Flipping: For the enhancement of various types of artificial images, the original images can be vertically or horizontally flipped as the positioning of this operation changes, while the features and components of the mean intensity values remain constant. Translation: the ROI of the actual images is shifted marginally in either the X or Y directions, or both. The values of the image component of the mean intensity are unchanged by the translation operation. The mathematical models for translation in image augmentation are listed in Equations.

$$X` = X + XT$$

$$Y` = Y + YT$$

where the original coordinates X and Y are the coordinates of X` and Y` in the new image denoted by the coordinates of a pixel, as XT and YT is translated by a distance in each direction expressed as correspondingly. The original datasets for each image (the conjunctiva of the eyes, palpable palm, and fingernails) were rotated 90° and 270°, flipped (mirrored/mirroring) using the vertical and horizontal methods, and translated to the X and Y axes.

High-performing algorithms may produce more precise predictions, analyse data more quickly, scale to handle large datasets, and be easier to understand, resulting in better outcomes and decision-making. In machine learning, classification models are commonly used to forecast outcomes based on a set of traits. [Ali et al., 2022, pp. 65–79] There are several widely used measures for assessing the performance of such models. The measure used is influenced by the nature of the problem, class balance, and the desired outcome of the model. A simple statistic called accuracy counts how many of the model's predictions were correct. When there is a class imbalance in the data, it may not be the best choice. When minimising false positives, precision refers to the percentage of true positives among all positive predictions made by the model [Emmanuel et al., 2022, pp. 9-22]. Recall, on the other hand, measures the proportion of true positives among all positive instances in the data and is useful when attempting to reduce false negatives.

Supervised learning algorithms, particularly Random Forest, were found to be effective for classifying types of anaemia from blood count data, with very high prediction accuracy. Implementing this system in areas with limited medical resources could significantly improve anaemia diagnosis and treatment outcomes. The findings highlight the significant potential for implementing artificial intelligence in medical diagnosis, as well as the accuracy and reliability of these models in clinical practice. It is important to note that this tool can only be used by medical personnel to speed up patient diagnosis. Data-driven machine learning involves computers learning and predicting. Machine learning classifies photographs by identifying objects, people, and other features. Picture classification employs supervised, unsupervised, and deep learning. CNN, Naïve Bayes and SVM models all improve image categorisation accuracy, efficiency, and robustness. Image machine learning is a rapidly expanding field that teaches computers visual information. Large photo datasets help algorithms identify patterns, objects, and complex relationships in images. These methods are applicable to image categorisation, object detection, segmentation, and creation.

5. Conclusions

Iron Deficiency Anaemia (IDA) is the most common haematological disorder caused by an iron deficiency, which is necessary for haemoglobin formation and oxygen transport in the body. A decrease in iron concentration reduces the number of RBCs and alters their shape and size. This study contributes to ongoing efforts to use machine learning and Explainable AI techniques to diagnose haemoglobin anaemia and iron serum levels. Our study demonstrated that the use of non-invasive approaches, such as machine learning algorithms, is effective, less costly, takes less time, and produces excellent results for anaemia detection. Furthermore, the goal of this research is to develop a cost-effective, result-oriented, and stress-free method for detecting anaemia in developing communities with limited health facilities, resources, and personnel. This would aid in the diagnosis and detection of anaemia, as well as the timely administration of treatment to anaemic patients. Comparing AI models such as CNN, Naïve Bayes and SVM models that used in our study for anemia diagnosis or definitely of iron levels detection is recommended because it allows you to evaluate the performance of each model and determine which one is the most accurate and reliable. This helps to ensure that the correct diagnosis is made and that the best treatment is administered. This aspect of AI programming entails collecting data and developing rules to convert it into actionable knowledge. Algorithms provide computer systems with detailed instructions for completing a specific task. By creating a predictive AI model that shows promise for improving diagnostic precision and clinical decision-making in anaemia management. The findings emphasise the value of interdisciplinary collaboration among data scientists, healthcare professionals, and researchers in addressing complex medical issues like anaemia. By leveraging data-driven approaches and advanced computational tools, healthcare systems can improve patient care, lower healthcare costs, and improve overall public health outcomes.

6. Future Research Directions Include the Following

Data expansion: It is recommended that additional and more diverse datasets be used to verify the model's accuracy in different demographic groups and regions, allowing for greater generalisation of the results and improving the model's robustness. Implementing explainable artificial intelligence techniques would assist medical professionals in better understanding the model's predictions, thereby increasing its reliability and transparency. Mobile device optimisation: Because many rural areas lack access to complete laboratories, it would be beneficial to adapt this system to mobile devices in order to facilitate their use in low-resource regions. Real-time assessment: By implementing a real-time assessment system, this model could be integrated into clinical settings that require rapid diagnoses, such as rural clinics or public health campaigns. These future directions may help to improve medical care in areas with limited access to diagnostic services, as well as optimise the use of resources in the healthcare sector.

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