Journal of Data Acquisition and Processing

ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.776691

UTILIZING MACHINE LEARNING TO DETECT ANEMIA

[1]Thakor kajal, [2] Dr. Swapnil M Parikh, [3] Dr. Vipul Dabhi, [4] Prof. Ankita Gandhi

[*] Computer Engineering Department, Parul Institute of Engineering and Technology, Parul University, Vadodara, Gujrat, India

*1) Corresponding author: thakorkajal6@gmail.com

2) swapnil.parikh17761@paruluniversity.ac.in

3) vipulkumar.dabhi23496@paruluniversity.ac.in

4) ankita.gandhi@paruluniversity.ac.in

ABSTRACT

Blood is a substance that moves waste materials from the cell and carries nutrition and oxygen to it. Blood is made up of platelets, which serve to halt hemorrhaging, red blood cells, which transport oxygen, and white blood cells, which act as the body's first line of defense against infectious diseases. The most prevalent blood condition, anemia, is brought on by a deficiency in red blood cells, which prevents the body from receiving enough oxygen. Chronic anemia results from a gradual decrease in red blood cells and is frequently associated with inflammatory diseases. Acute anemia is caused by a sudden drop in RBCs. In order to identify and categories anemia, this study applies machine learning techniques such as K-nearest neighbors (KNN), Naive Bayes, and decision trees. States/UTs, Area, and other monitoring data were used as input for evaluation. Infants aged 6 to 59 months (about 5 years) with anemia (11.0 g/dl), Non-pregnant women aged 15 to 49 with anemia (12.0 g/dl), Pregnant women aged 15 to 49 with anemia (11.0 g/dl), All women aged 15 to 49 with anemia (11.0 g/dl) All ladies between the ages of 15 and 19 who are anemic : 22 (%) Males aged 15 to 49 who are anemic (13.0 g/dl) make up 22 (%), as do men aged 15 to 19 who are anemic (13.0 g/dl). The study's findings point to a wide range of potential uses for this technology in the area of medical diagnosis.

Keywords: Machine Learning, Anemia, Extraction, Identification

I. INTRODUCTION

The most prevalent blood disorder worldwide is anemia. The World Health Organization (WHO) defines anemia as a situation where there are not enough red blood cells and, as a result, not enough of them can transport enough oxygen to satisfy the body's physiological requirements. Another definition of anemia is a reduction in blood hemoglobin and hematocrit levels as well as cell bulk. Age and gender-specific numbers for normal hemoglobin and hematocrit exist. Anemia is prevalent if the values of the hemoglobin and hematocrit are below the cutoff of what is considered typical for the age and sex. Using information and resources from the 2010 WHO research on the global burden of illness, Kiassebaum et al. looked at 189 nations, both sexes, and 20 distinct age groups. They determined that 32.9% of people worldwide have anemia. Children under five and women are the most likely to experience anemia. Iron-deficiency anemia is the form of anemia that is most seen. The treatment of anemia, which has a major negative impact on quality of life and is both an illness and a symptom of many severe diseases, can often be life-saving, making a proper evaluation the first step in treatment.

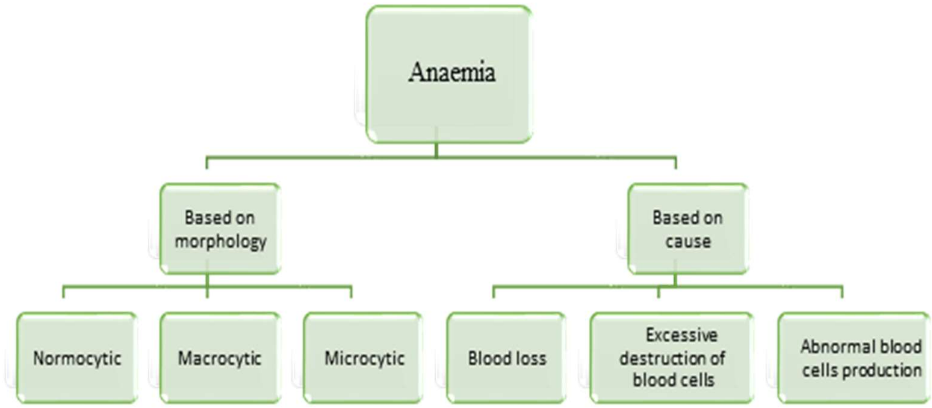

Figure. 1: Classification of anemia

Predicting anemia illness is crucial for finding other related diseases. Anemia is categorized according to its morphology or fundamental reason (Fig 1). Anemia is classified into three groups based on morphology: normocytic, microcytic, and macrocytic. Anemia is divided into three categories based on its underlying causes: blood loss, insufficient generation of healthy blood, and excessive blood cell apoptosis.

Using data gathered from the NFHS, we try to compare the effectiveness of the Naive Bayes, Random Forest, and Decision Tree algorithms in this article for the forecast of anemia illness. The reality that the disease's fundamental cause differs from region to region necessitates this study. Although the random forest classifier has previously been studied for the forecast of heart and chronic renal disease, as far as we are aware, it has not been studied for the prediction and categorization of anemia disease. This makes the product more unique.

II. LITERATURE SURVEY

Numerous data mining, deep learning, artificial intelligence, and machine learning methods have been applied to the treatment of anemia over the past ten years. The following are most prominently mentioned:

To evaluate images, [1] implements the k closest Neighbors (k-NN), support vector machine (SVM), and extreme learning machine (elm) classifiers. This method displays comparisons between the classifiers with accurate findings. Compared to k closest neighbor and support vector machines, radical learning machines are generally better.

[2] uses a machine learning method to identify anemia. The purpose of the article is to offer a remote, non-invasive, standard method that allows a fast screening to find hemoglobin levels using smartphones and AI techniques. The conjunctiva of the eye is mechanically removed as a Region of Interest from the picture of the eye after it has been photographed (ROI). Following processing, features are taken from the ROI to programme a machine-learning

system to determine whether the patient is anemic or not. The model's accuracy, precision, and memory were all 85%, and it covered 200 topics.

Based on 539 data points with 10 attributes that were gathered from labs, Mohammed Sami MOHAMMED [3], Bayesian Network (BN), Naive Bayes (NB), Logistic Regression (LR), and Multilayer Perceptron (MLP) have been used to forecast anemia. When compared to other techniques, the LR has produced superior outcomes.

Anemia has been predicted using Pooja Tukaram Dalvi, Nagaraj Vernekar [4], Decision Tree, Artificial Neural Network, Naive Bayes, and K-Nearest Neighbor algorithm. The Artificial Neural Network performs the best and K-Nearest Neighbor performs the worst among the separate classifiers. However, when used on a stacking ensemble, the classifier combo of Decision Tree and K-Nearest Neighbor gets a much better accuracy than the Artificial Neural Network. This shows that a group of classifiers performs much more accurately than a single classifier. Therefore, an array of classifiers should be used to attain the highest level of precision in medical decision-making.

In [5], This study describes the use of K-nearest neighbors (KNN), a machine learning technique, to identify and categories anemia. The study's findings point to a wide range of potential uses for this technology in medical diagnosis.

Manish Jaiswal, Anima Srivastava and Tanveer J. Siddiqui [6], In this research, we use CBC (complete blood count) data obtained from pathology facilities to explore supervised machine learning algorithms—Naive Bayes, Random Forest, and Decision Tree Algorithm—for anemia prediction. The outcomes demonstrate that the Naive Bayes method beats C4.5 and random forest in terms of accuracy.

In [7], For the forecast of anemia, supervised machine learning methods include the Naive Bayes, LR, LASSO, and ES algorithms. And assume that the patient will either be cured or uncured after 90 days (about 3 months). The outcomes indicate that the Naive Bayes method excels in terms of accuracy when compared to LR, LASSO, and ES.

Anemia and starvation are identified using machine learning, according to Richard Joseph, Vedant Sawant, and Shivani Shenai [8]. To find the different factors affecting malnutrition and connect its relationship with anemia, which has not yet been tied to existing literature, this study uses the machine learning method. Additionally, the extent to which these characteristics impact malnutrition is determined, and geographically specific characteristics are targeted for children residing in different Indian states.

Bheem Sen, Adarsh Ganesh, Anupama Bhan [9], used machine learning method to identify anemia. The automated identification of sickle cells in microscopic pictures is done in this study using image processing and machine learning methods, which then categories the RBC into three different forms: circular, elongated (sickle cell), and other shapes.

In [10], In this research, we use CBC (complete blood count) data obtained from pathology facilities to explore supervised machine learning algorithms—Naive Bayes, Random Forest, and Decision Tree Algorithm—for anemia prediction. The outcomes demonstrate that the Naive Bayes method beats C4.5 and random forest in terms of accuracy.

In [11], create a curate anaemia prediction system, three based rule categorization methods are used: ZeroR, OneR, and PART to select pertinent anemia datasets linked with "If" and "Then" procedures. In terms of the methods used, PART offered 85% more precision than

ZeroR and OneR. These methods offered a standard for other methods that were used to explain the necessary understanding of anemia data principles.

[12], utilizes the WEKA data-mining tool along with a few categorization methods, including Naive Bayes, Multilayer Perception, J48, and SMO. The J48 decision tree method provides the greatest possible classification of anemia types, according to numerous tests. This study uses a predictive model and data mining classification methods to identify the specific form of anemia in anemic individuals.

N. Sasikala, Gulmohamed Rasitha Banu [13], Using scientific research is conducted data extraction methods like J48 and Random Forest trees also a hoeffding tree. Consequently, the show is three categorization methods were examined for them comparison of precision using an uncertainty matrix. Random Forest tree provides greater accuracy, it has been determined. compared to the J48 and Hoeffding tree method.

Three data mining classifiers—Decision Tree, Rule Induction, and Naive Bayes—are used in [14]. The results demonstrate that Rule induction classifier performs better in predicting Hematology (Adult, Children) with accuracy of (57%-67%) than Nave Bayes classifier (accuracy of 56% for tumor of blood disease), while Decision Tree has the lowest accuracy rate for detecting the three types of diseases in our dataset.

Laengsri V, Shoombuatong W [15], A classifier model was built using five machine learning techniques: k-nearest neighbor (k-NN), decision tree, random forest (RF), artificial neural network (ANN), and support vector machine (SVM). The effectiveness of the system was evaluated and compared to thirteen pre-existing diagnostic indices and algorithms.

In this article, we analyze the prediction and categorization of anemia in patients using data mining methods, as described in [16]. Based on CBC reports and anemia severity, a decision tree for anemia categorization is created. This decision tree provides the finest anemia classification available. We have found that the C4.5 algorithm performs best and is most accurate.

K. Dinakaran and R. Preethi [17], The current research suggests a novel approach for locating possible data on blood-related diseases. Maximizing Expectations Together, the clustering algorithm and the k-Means clustering algorithm successfully group the patients based on their characteristics. It has been demonstrated that improved data yields the best results and may help the medical community identify a group of patients.

Srdjan Denic,1 Mukesh M. Agarwal,2 [18], The goal of this research was to investigate some possible factors that could have an impact on HbA2 and what that might mean for BTT screening. It is reasonable to regularly measure serum ferritin in females because iron deficiency is mostly restricted to females. Additionally, all individuals without BTT who intend to marry BTT carriers should get a Genetic test for the -thalassemia mutation. This is because marriage between two BTT carriers can be devastating for the offspring. This method of BTT screening needs to have its benefits supported by bigger research.

Thomas H. A. Ederveen , Fajar Agung Nugroho, [19], This research used a computational model to identify a causative relationship between gut microbiome profiles, RTI and systemic inflammation factors, and the efficacy of iron supplementation. The relationship between clinical factors and iron-micronutrient supplementation in infants with iron deficiency anemia was discovered through computer modelling. The biological basis of RTI, the change of the gastrointestinal flora, and iron supplementation may all be better understood because of more targeted research.

In [20] By building a device using a Raspberry Pi that can measure the different parameters of the RBC such as area, perimeter, diameter, shape geometric factor (SGF), and detecting the central pallor and target flag, a proposed system is intended to assist medical technicians, hematologists, and pathologists in identifying RBC. This method only assists medical professionals in the early diagnosis of abnormal red blood cells; further laboratory tests must be performed to definitively identify an illness linked to abnormal RBCs.

[21], data mining methods are used to operate the system, with pattern recognition as the system's operating system. Artificial Neural Networks were able to achieve the best efficiency data mining techniques (78.31). In this manner, biochemical parameters have been demonstrated to be useful for identifying iron deficiency anemia and will assist the doctor in starting an efficient course of therapy for the patient.

Kanak Meena [1], Devendra K Tayal [2] [22], With the goal of lowering the risk of blood-related illness anemia, the two-methods decision tree and association rule mining have been applied and contrasted to determine which is more suitable for this specific task.

[23] In this research, there were 104 54 men and 50 women are gathered with their health data. blood hemoglobin content, anemia, and palpebral examination conjunctiva picture. For detecting anemia, the 81 samples are educated using a variety of classifiers, including Cosine K NN, Linear SVM, and Coarse Tree have been obtained. best accuracy of 82.61% in trials for Decision Tree (Coarse) 23 data.

[24], The method suggested in the current study will make it possible to identify anemia in routine clinical practice settings. A model created for this system using four distinct machine learning techniques. As categorization systems, Artificial Neural Networks, Support Vector Machines, Naive Bayes, and Ensemble Decision Tree techniques are employed. Bagged Decision Trees had the best accuracy (85.6%), followed by Boosted Trees (83.0%) and Artificial Neural Networks (79.6%).

III. METHODOLOGY

Dataset Collection:

In-depth patient data from the research was utilized in the study. As a result, we sought the advice of a qualified medical expert and identified the characteristics she used to identify different forms of anemia. The dataset's Gender, Hemoglobin, MCH, MCHC, MCV, TYPE, and Result characteristics are all utilized.

Pre-Processing:

The proposed method uses CBC test values. First, the data are pre-processed to extract. Then, we apply the Random Forest, Decision tree, KNN, Linear SVM, Logistic Regression, Radial SVM, NB classifier on it. The performance evaluation is done in terms of accuracy and mean absolute error (MAE). The mean absolute error (MAE) measures how close the predictions are to the eventual outcomes. A summary of the three classifiers findings. Accuracy has been attained using tenfold cross-validation. The comparison of each classification algorithm's accuracy and MAE performance.

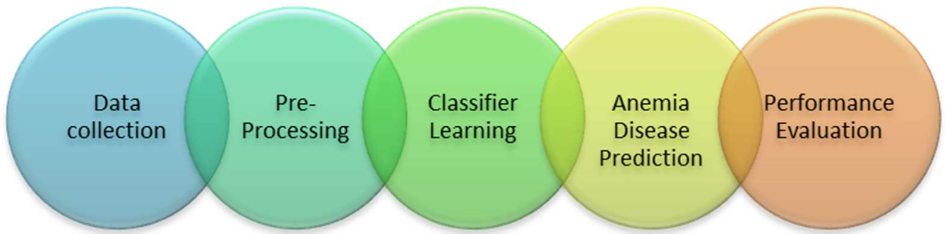

Figure. 2: Proposed diagram

Classification:

In the current study, the effectiveness of well-known classification techniques was assessed by producing an entirely new dataset. KNN, support vector machines, decision trees, and naive bayes are selected as the classifiers since they are frequently utilized in literature. These cutting-edge categorization techniques produce encouraging results. Additionally, it has been established that these techniques work well when applied to medical data. Consequently, various techniques are used, and the outcomes are contrasted.

Random forest:

The decision tree classification is the ancestor of the random forest (RF) method. It is a combination of tree predictors that employs majority polling to determine and combines the outcomes of all the trees in the collection.

Decision Tree:

A decision tree is a tree in which each leaf node represents a judgement, and each branch node

represents an option among several possibilities. It has been widely applied in many different areas. Ross Quinlan created the decision tree C4.5 (J48 in WEKA).
Naive Bayes Algorithm

Naïve Bayes:

The Bayes rule of conditional probability is the foundation of the Naive Bayes algorithm. It makes use of every characteristic in the data and examines each one separately because they are all equally significant and independent of one another. Very little training material is needed.

LINEAR SVM

The term "linearly separable data" refers to data that can be divided into two groups using only a single straight line. Linear SVM is used to classify such data, and the classifier utilized is known as the Linear SVM classifier.

LOGISTICS REGRESSION

A primary use for the supervised machine learning technique known as logistic regression is classification tasks, where the objective is to determine whether a given instance will belong to a certain class or not. It is a type of statistical technique that examines the correlation between several independent factors and the dependent binary variables. It is an effective instrument for making decisions.

RADIAL SVM

When the data cannot be separated linearly, a radial kernel SVM is a useful solution. Making nonlinear modifications to the characteristics Xi to place them in a higher dimensional space is the rationale underlying creating nonlinear decision boundaries.

IV. MODEL EVALUATION METRICS

Numerous indicators are available to assess machine learning models in diverse applications. Let's examine the evaluation metrics to evaluate a machine learning model's performance. This is essential in any data science project because it seeks to estimate a model's generalization accuracy on future data.

A. Precision

Accuracy can become an unreliable criterion for gauging our success when there is a class imbalance. As a result, we also need to consider class-specific performance indicators. One of these measurements, called precision, is defined as positive predicted values.

$$PRICISION = \frac{TRUE\ POSITIVE}{(TRUE\ POSITIVE\ +\ FALSE\ POSITIVE)}$$

B. Recall

A recall is another crucial indicator; it measures the percentage of real positive cases that were accurately identified.

$$RECALL = \frac{TRUE\ POSITIVE}{(TRUE\ POSITIVE\ +\ FALSE\ NEGATIVE)}$$

C. F1-score

Precision and Recall are two significant error metrics that make up the F1 score together. In light of binary data categorization, it can be seen as the Harmonic Mean of Precision and Recall error metrics for an unbalanced dataset.

$$F1\ SCORE = \frac{2 * PRECISION * RECALL}{PRECISION\ +\ RECALL}$$

D. Accuracy

An indicator of the model's performance across all classes is accuracy. When all types are equally important, it is helpful. It is calculated by ÷ the total number of % by the number of accurate forecasts.

$$ACCURACY = \frac{TP + TN}{(TP\ + TN +\ FP +\ FN)}$$

E. Mean Average Precision

It is a well-liked evaluation metric for object detection in computer vision. An instance's localization pinpoints its precise location, whereas its classification identifies its nature.

$$mAP = 1 \sum_{i=1} AP_i$$

V.OBSERVATIONS, RESULTS AND DISCUSSION

We have analyzed the results from Accuracy, Precision, and Recall by comparing them with other ML algorithms.

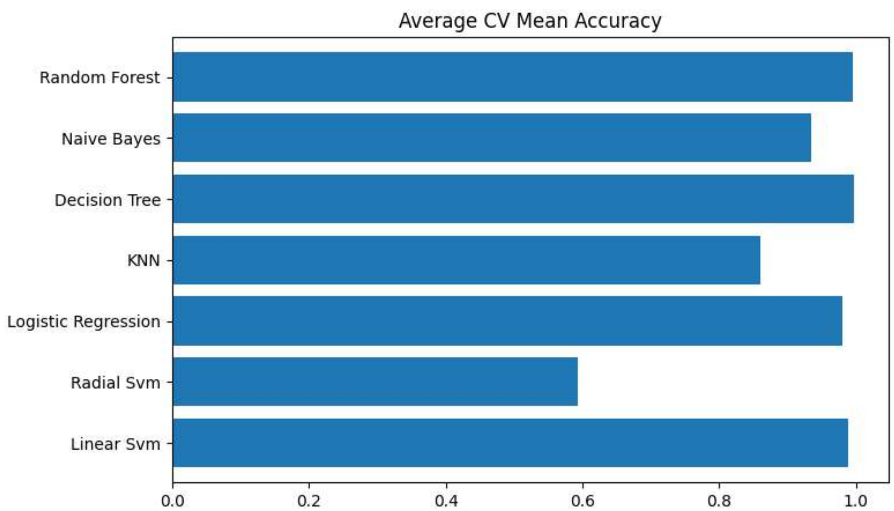

Figure. 3: Proposed Model Accuracy

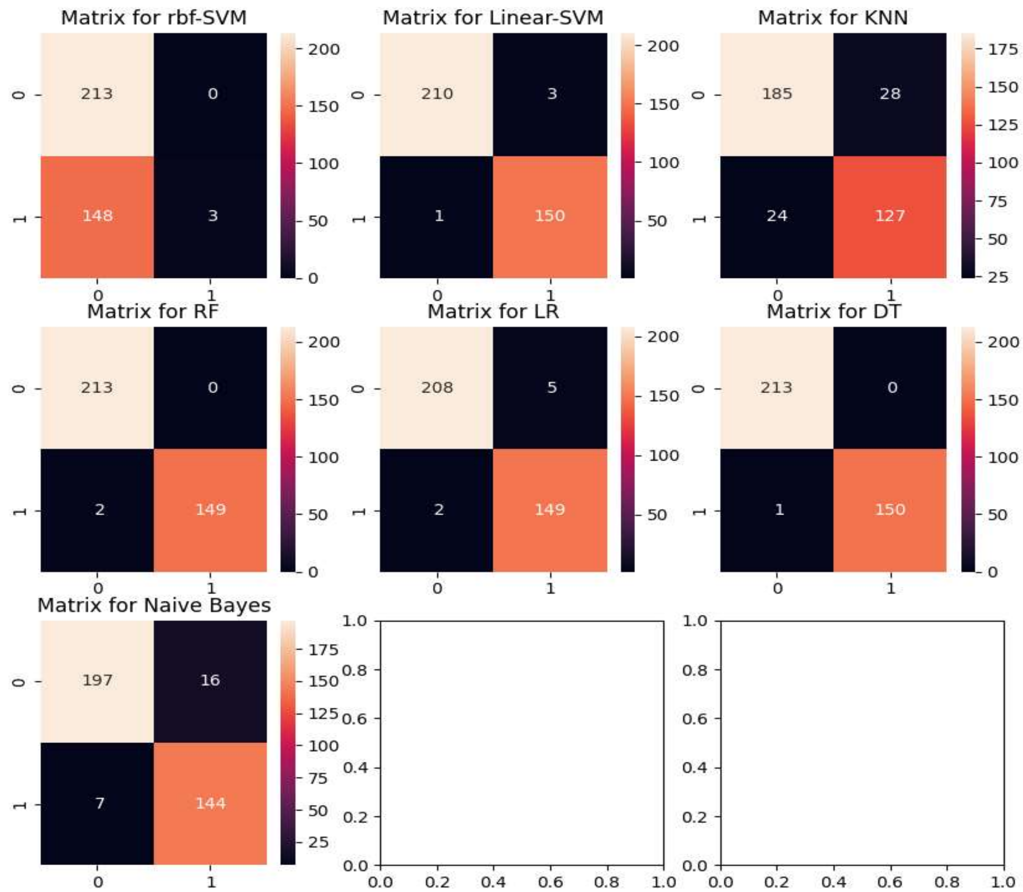

Figure. 4: confusion Matrix of classifier

Table 1: Comparison of algorithm

Algorithm	Accuracy	Precision	Recall
Logistic Regression	97%	97%	97%
Radial SVM	90%	91%	91%
KNN	80%	81%	81%
Decision Tree	99%	99%	99%
Random forest	99%	99%	99%
Linear SVM	96%	97%	96%
Naive Bayes	89%	87%	89%

VI. CONCLUSION

In this study, we evaluated the accuracy of several classifiers in predicting anaemia sickness. The experimental outcome on a test dataset indicates that, when compared to Random Forest, Naive Bayes, Linear SVM, Logistic Regression and Radial SVM, the Decision Tree classification method performs best in terms of accuracy. Automatic prediction can lessen the amount of manual work required for diagnosis. In the future, automated technologies may be created to assist in suggesting additional diagnoses based on the predictions. These automated technologies may be useful in the early identification of more serious diseases. Such a disease prediction system can also suggest a treatment strategy.

VII. REFERENCES

1. S. C, A. M. R, D. M. D and D. M, "Curability Prediction Model for Anemia Using Machine Learning," *2022 8th International Conference on Smart Structures and Systems (ICSSS)*, Chennai, India, 2022, pp. 1-7, doi: 10.1109/ICSSS54381.2022.9782233.
2. B. Sen, A. Ganesh, A. Bhan, S. Dixit and A. Goyal, "Machine learning based Diagnosis and Classification Of Sickle Cell Anemia in Human RBC," *2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, Tirunelveli, India, 2021, pp. 753-758, doi: 10.1109/ICICV50876.2021.9388610.
3. R. Joseph, V. Sawant, S. Shenai, M. Paryani and G. Patil, "Machine Learning based Factors affecting Malnutrition and Anemia among children in India," *2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, 2022, pp. 1826-1833, doi: 10.1109/ICICCS53718.2022.9788386.
4. P. T. Dalvi and N. Vernekar, "Anemia detection using ensemble learning techniques and statistical models," *2016 IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)*, Bangalore, India, 2016, pp. 1747-1751, doi: 10.1109/RTEICT.2016.7808133.
5. S. H.Elgohary, Z. A. Mohamed, O. A. Mohamed, A. O. Ismail, A. G. Elmahdy and M. I. Basheer, "A Machine Learning Method to Screen Anemia From Conjunctiva Images Taken by Smartphone," *2022 10th International Japan-Africa Conference on Electronics, Communications, and Computations (JAC-ECC)*, Alexandria, Egypt, 2022, pp. 125-128, doi: 10.1109/JAC-ECC56395.2022.10043861.
6. A. Kovačević, A. Lakota, L. Kuka, E. Bečić, A. Smajović and L. G. Pokvić, "Application of Artificial Intelligence in Diagnosis and Classification of Anemia," *2022 11th Mediterranean Conference on Embedded Computing (MECO)*, Budva, Montenegro, 2022, pp. 1-4, doi: 10.1109/MECO55406.2022.9797180.
7. Appiahene, P., Asare, J.W., Donkoh, E.T. *et al.* Detection of iron deficiency anemia by medical images: a comparative study of machine learning algorithms. *BioData Mining* **16**, 2 (2023). https://doi.org/10.1186/s13040-023-00319-z
8. Jaiswal, Manish & Srivastava, Anima & Siddiqui, T.J.. (2019). Machine Learning Algorithms for Anemia Disease Prediction: Select Proceedings of IC3E 2018. 10.1007/978-981-13-2685-1_44.

9. M. S. MOHAMMED, A. A. AHMAD and M. SARI, "Analysis of Anemia Using Data Mining Techniques with Risk Factors Specification," *2020 International Conference for Emerging Technology (INCET)*, Belgaum, India, 2020, pp. 1-5, doi: 10.1109/INCET49848.2020.9154063.

10. Jaiswal, M., Srivastava, A., & Siddiqui, T. J. (2018). Machine Learning Algorithms for Anemia Disease Prediction. Recent Trends in Communication, Computing, and Electronics, 463–469. doi:10.1007/978-981-13-2685-1_44

11. S. J. Mohammed MOHAMMED, A. A. Ahmed, A. A. Ahmad and M. Sami MOHAMMED, "Anemia Prediction Based on Rule Classification," 2020 13th International Conference on Developments in eSystemsEngineering (DeSE), 2020, pp. 427-431, doi: 10.1109/DeSE51703.2020.9450234.

12. Abdullah, Manal& Al-Asmari, Salma. (2016). Anemia types prediction based on data mining classification algorithms.

13. Sasikala, N. &Banu, Gulmohamed&Babiker, Thgani&Rajpoot, Pushp. (2021). A Role of Data Mining Techniques to Predict Anemia Disease. International Journal of Computer Applications. 174. 16-20. 10.5120/ijca2021921090

14. A. H. Shurrab and A. Y. A. Maghari, "Blood diseases detection using data mining techniques," 2017 8th International Conference on Information Technology (ICIT), 2017, pp. 625-631, doi: 10.1109/ICITECH.2017.8079917.

15. Laengsri, V., Shoombuatong, W., Adirojananon, W. *et al.*ThalPred: a web-based prediction tool for discriminating thalassemia trait and iron deficiency anemia. *BMC Med Inform DecisMak***19**, 212 (2019).

16. Sanap, S.A., Nagori, M., Kshirsagar, V. (2011). Classification of Anemia Using Data Mining Techniques. In: Panigrahi, B.K., Suganthan, P.N., Das, S., Satapathy, S.C. (eds) Swarm, Evolutionary, and Memetic Computing. SEMCCO 2011. Lecture Notes in Computer Science, vol 7077. Springer, Berlin, Heidelberg.

17. Dinakaran, K. &Preethi, R.. (2013). A Novel Approach to Uncover the Patient Blood Related Diseases using Data Mining Techniques. Journal of Medical Sciences(Faisalabad). 13. 95-102. 10.3923/jms.2013.95.102.

18. SrdjanDenic, Mukesh M. Agarwal, Bayan Al Dabbagh, Awad El Essa, Mohamed Takala, SaadShowqi, JavedYassin, "Hemoglobin A_2 Lowered by Iron Deficiency and α-Thalassemia: Should Screening Recommendation for β-Thalassemia Change?", *International Scholarly Research Notices*, vol. 2013, Article ID 858294, 5 pages, 2013.

19. F. A. Nugroho, T. H. A. Ederveen, A. Wibowo, J. Boekhorst, M. I. de Jonge and T. Heskes, "Application of A Causal Discovery Model to Study The Effect of Iron Supplementation in Children with Iron Deficiency Anemia," 2019 3rd International Conference on Informatics and Computational Sciences (ICICoS), 2019, pp. 1-5, doi: 10.1109/ICICoS48119.2019.8982503.

20. C. C. Hortinela, J. R. Balbin, J. C. Fausto, P. Daniel C. Divina and J. P. T. Felices, "Identification of Abnormal Red Blood Cells and Diagnosing Specific Types of Anemia Using Image Processing and Support Vector Machine," 2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM), 2019, pp. 1-6, doi: 10.1109/HNICEM48295.2019.9072904.

21. .T. İlaslaner and A. Güven, "Investigation of the Effects Biochemistry on Iron Deficiency Anemia," 2019 Medical Technologies Congress (TIPTEKNO), 2019, pp. 1-4, doi: 10.1109/TIPTEKNO.2019.8895227.

22. .Meena K, Tayal DK, Gupta V, Fatima A. Using classification techniques for statistical analysis of Anemia. ArtifIntell Med. 2019 Mar;94:138-152. doi: 10.1016/j.artmed.2019.02.005. Epub 2019 Feb 19. PMID: 30871679.

23. . Noor, Nahiyan& Anwar, Mohammad &Dey, Mrinmoy. (2019). Comparative Study Between Decision Tree, SVM and KNN to Predict Anaemic Condition. 10.1109/BECITHCON48839.2019.9063188.

24. K.Y., Tuba &Yurtay, Nilüfer&Öneç, Birgül. (2021). Classifying anemia types using artificial learning methods. Engineering Science and Technology, an International Journal. 24. 50-70. 10.1016/j.jestch.2020.12.003.

25. W. Yu *et al.*, "Automatic classification of leukocytes using deep neural network," *2017 IEEE 12th International Conference on ASIC (ASICON)*, Guiyang, China, 2017, pp. 1041-1044, doi: 10.1109/ASICON.2017.8252657.

26. C. Bellinger, A. Amid, N. Japkowicz and H. Victor, "Multi-label Classification of Anemia Patients," *2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA)*, Miami, FL, USA, 2015, pp. 825-830, doi: 10.1109/ICMLA.2015.112.

27. Z. Liu *et al.*, "Prevalence and related factors of anemia among human immunodeficiency virus(HIV)/acquired immune deficiency syndrome (AIDS) outpatients in resources limited region of China," *2013 IEEE International Conference on Bioinformatics and Biomedicine*, Shanghai, China, 2013, pp. 157-161, doi: 10.1109/BIBM.2013.6732663.

28. C. Sotomayor-Beltran and G. Z. Segura, "A spatial assessment of anemia among Peruvian children aged 6 months to 5 years between 2016 and 2017," *2018 Congreso Argentino de Ciencias de la Informática y Desarrollos de Investigación (CACIDI)*, Buenos Aires, Argentina, 2018, pp. 1-5, doi: 10.1109/CACIDI.2018.8584359.

29. C. Sotomayor-Beltran and G. Z. Segura, "A spatial assessment of anemia among Peruvian children aged 6 months to 5 years between 2016 and 2017," *2018 Congreso Argentino de Ciencias de la Informática y Desarrollos de Investigación (CACIDI)*, Buenos Aires, Argentina, 2018, pp. 1-5, doi: 10.1109/CACIDI.2018.8584359.

30. I. Uvaliyeva, S. Belginova, S. Rustamov and A. Ismukhamedova, "Algorithm Diagnosis of Anemia on the basis of the Method of the Synthesis of the Decisive Rules," *2019 IEEE 13th International Conference on Application of Information and Communication Technologies (AICT)*, Baku, Azerbaijan, 2019, pp. 1-5, doi: 10.1109/AICT47866.2019.8981766.

31. J. Punter-Villagrasa, J. Cid, J. Colomer-Farrarons, I. Rodríguez-Villarreal and P. L. Miribel-Català, "Toward an Anemia Early Detection Device Based on 50-µL Whole Blood Sample," in *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 2, pp. 708-716, Feb. 2015, doi: 10.1109/TBME.2014.2364139.

32. C. Sotomayor-Beltran, G. W. Zarate Segura and D. Tarazona, "Anemia During Pregnancy in Peru in 2017: A Geographic Information System Study," *2018 IEEE 38th Central America and Panama Convention (CONCAPAN XXXVIII)*, San Salvador, El Salvador, 2018, pp. 1-5, doi: 10.1109/CONCAPAN.2018.8596336.

33. M. Oktavianus *et al*., "Diagnosis Of Anemia In Expert System Programming With Certainty Factor," *2021 3rd International Conference on Cybernetics and Intelligent System (ICORIS)*, Makasar, Indonesia, 2021, pp. 1-6, doi: 10.1109/ICORIS52787.2021.9649593.

34. E. Stoyanova, M. Trudel, F. S. Foster and G. Cloutier, "Comparison of Doppler ultrasound flow resistance indices in beta-thalassemic, sickle cell anemic and control mice," *2004 2nd IEEE International Symposium on Biomedical Imaging: Nano to Macro (IEEE Cat No. 04EX821)*, Arlington, VA, USA, 2004, pp. 956-959 Vol. 1, doi: 10.1109/ISBI.2004.1398698.