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Machine Learning Approaches for Enhanced Diagnosis of Hematological Disorders

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ABSTRACT This research examined the feasibility of utilizing ML algorithms to improve the initial detection and classification of anemia and other blood disorders. The following study employed several traditional machine learning models: additional ML and AI methods were subsequently evaluated including - LightGB, CatBoost, Decision Tree, Gradient Boosting, Random Forest and XGBoost to blood-based features (RBC, WBC, HGB, and PLT). The results demonstrated that LightGB had the highest accuracy of 98.38%, then followed by CatBoost at 98.37%. The Decision Tree and Gradient Boosting models respectively demonstrated an accuracy of 98.05%. The accuracy of Random Forest and XGBoost was 97.72%. These results show the possibility of ML techniques being able to uncover higher-level complex patterns in medical data to improve accuracy, particularly for anemia. The study presented new evidence and baseline models to promote ML to expedite clinical decision making to provide timely intervention and develop personalized health care. The study provided evidence and potential usages for ML models to enable better clinical decision and action. The findings of this study explained that in the future using advanced technologies or deep learning, or addressing concerns relating to explainable AI methods, the capabilities in clinical use should be optimized and expanded.

KEYWORDS
Anemia
Machine learning (ML)
Blood disorders
Clinical decision support
Hematological data

INTRODUCTION

Anemia is recognized as one of the most prevalent blood disorders around the world, affecting people of all ages. Anemia can be defined primarily by a loss of red blood cells or hemoglobin, and associated symptoms commonly include fatigue, dizziness, and pallor (Yoshida 2024) . Additionally, different forms of anemia are attributed to heterogeneous causes including nutritional deficits, chronic disease, inherited conditions and bone marrow disorders (Krieg *et al.* 2024). Anemia is also studied and examined in conjunction with other hematologic conditions including leukemia, thrombocytopenia, and macrocytic anemia that need to be crudely and accurately classified to ensure timely diagnosis and treatment (Fentie *et al.* 2020; Subba and Araveti 2025).

A complete blood count (CBC) test is a commonly used measure to diagnose anemias and blood-related conditions, which provides important measures including two types of blood cells, namely red and white blood cells, hemoglobin, hematocrit and two parts of the blood (platelets) (Karra *et al.* 2025; Malak *et al.* 2025; Li *et al.* 2025). Nevertheless, accurate diagnostic interpretation of these tests is difficult due to the increasing data generated by more complex patient data and higher volume of patients. Machine learning (ML) and deep learning (DL) have recently been used in nearly every field (Zeynalov *et al.* 2025). In particular, they have proven to be effective methods for analyzing healthcare data (Pacal 2025; Cakmak and Pacal 2025; Cakmak *et al.* 2024). With fast, efficient, reproducible, and cost-effective decisions supporting clinical judgment (Link *et al.* 2024), it is an excellent option in the classification of blood disorders. In the current study, we have provided an assessment of common ML algorithms to classify anemia and associated hematologic disorders. We found that LightGBM had the highest all in all accuracy (98.38%) followed closely by CatBoostClassifier (98.38%), Decision Tree and Gradient Boosting (98.05%), Random Forest and XGBoost (97.73%) (Ramzan *et al.* 2024; Kitaw *et al.* 2024). Thus, we have shown that ML models provide highly accurate classifications, potentially enabling a more timely diagnosis and treatment.

Similar success patterns have been documented in earlier studies. For example, Sanap et al. used CBC data to develop a classificatory model for anemia types using the C4.5 decision tree (J48) and Support Vector Machine (SMO) algorithms in the Weka environment, and found that C4.5 had better classification accuracy than SVM (Sanap *et al.* 2011). In a subsequent study, the same authors compared Naïve Bayes, Random Forest, and Decision Tree algorithms, concluding that Naïve Bayes offered superior performance (Jaiswal *et al.* 2018). These findings reinforce the value of lightweight, probabilistic models for clinical classification tasks. Kanak et al. explored childhood anemia, focusing on the influence of maternal health and nutrition during pregnancy. Using NFHS-4 survey data, they constructed a decision support system aimed at both prediction and prevention, comparing decision trees and association rule mining to determine the most effective modeling technique (Meena *et al.* 2019). Tuba et al. developed a machine learning-based decision support system trained on 1,663 patient

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records from a hospital in Turkey. Their model aimed to classify 12 types of anemia based on hemogram features and patient history. Among the four algorithms evaluated, Bagged Decision Trees achieved the highest accuracy (85.6%), followed by Boosted Trees (83.0%) and Artificial Neural Networks (79.6%) (Yıldız *et al.* 2021). Their approach was designed to assist both clinicians and medical students in diagnostic processes.

In another contribution, Justice et al. offered a comprehensive review of ML applications in anemia detection, emphasizing the accessibility and affordability of such methods, particularly in low-resource settings. Their analysis highlighted the practical advantages of ML over traditional diagnostic methods, especially in terms of early detection and broader clinical applicability (Asare *et al.* 2023). Lastly, Serhat et al. introduced two hybrid deep learning models GA-SAE and GA-CNN that leverage genetic algorithms to optimize hyperparameters in Stacked Autoencoders and Convolutional Neural Networks. Their work addressed the variability in datasets and targeted the classification of HGB-based anemia, nutritional deficiencies (iron, B12, folate), and non-anemic cases. Their GA-CNN model achieved a notable accuracy of 98.50%, outperforming conventional models across multiple evaluation metrics (Kilicarslan *et al.* 2021). Taken together, these studies reflect a growing consensus around the efficacy of ML in hematological diagnostics. The results of our own research align with this broader trend, demonstrating that well-selected ML models can serve as effective, supportive tools in the early and accurate classification of anemia and related disorders. As healthcare systems continue to integrate data-driven approaches, such models are likely to play an increasingly prominent role in clinical workflows (Rekaya *et al.* 2025; Chandra *et al.* 2022; Ozdemir *et al.* 2025; Pacal and Karaboga 2021).

MATERIALS AND METHODS

Dataset

In this study, we worked with a dataset comprising 1,281 instances and 15 distinct features to explore the classification of anemia and related hematological conditions. After removing 49 duplicate entries, a total of 1,232 unique samples were retained for training and evaluation of the models. The dataset encompasses a variety of diagnostic categories, including Healthy, Iron Deficiency Anemia, Leukemia, Leukemia with Thrombocytopenia, Macrocytic Anemia, Normocytic Hypochromic Anemia, Normocytic Normochromic Anemia, Other Microcytic Anemia, and Thrombocytopenia (Aboelnaga 2024) .

The primary objective of this research is to apply ML algorithms to distinguish among these different anemia types. Given that anemia represents a widespread public health concern, especially in low- and middle-income regions, timely diagnosis and precise classification are critical for guiding appropriate treatment strategies. By improving diagnostic accuracy through computational models, healthcare providers can make more informed decisions, ultimately leading to more effective care and improved patient outcomes. A visual representation of the class distribution in the dataset is provided in Figure 1.

Characteristics and Classes of The Dataset

This research explores the essential hematological characteristics that contribute significantly to the classification of anemia and other related blood disorders. These features offer valuable insights into the various components and functions of blood cells. An overview of these characteristics, along with their respective attributes, is presented in Table 1.

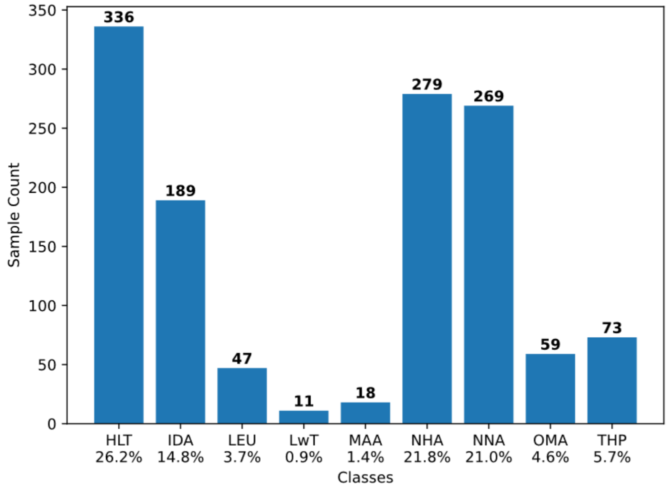


Figure 1 The distribution of classes in the dataset used in the study is shown

Data Preprocessing Steps

To prepare the dataset for effective model training, a series of preprocessing steps were carried out to improve both data quality and model performance. As a first step, missing values were addressed either by removing incomplete rows or by applying imputation techniques, such as replacing missing entries with the mean or median of the respective feature. To standardize the scale across all variables particularly important for distance-based algorithms feature scaling was performed. Categorical features were transformed into numerical form through encoding strategies like one-hot encoding or label encoding. Since the target labels were already in a format suitable for classification, no logarithmic transformation was necessary.

Moreover, to eliminate redundancy and potential bias, 49 duplicate entries were identified and removed from the dataset. Following this cleaning process, the dataset was divided into training and testing subsets, with 75% allocated for training and the remaining 25% reserved for evaluation, as illustrated in Figure 2.

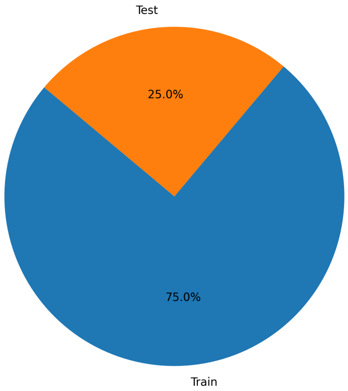


Figure 2 The dataset used in the study was divided into train 75% and test 25%

Table 1 Dataset features and descriptions

Features	Description
WBC	White Blood Cell count, indicating the number of white blood cells in the blood, used to assess immune function.
LYMp	Percentage of lymphocytes in the total white blood cell count, indicating immune response.
NEUTp	Percentage of neutrophils in the total white blood cell count, associated with bacterial infections.
LYMn	Absolute number of lymphocytes in the blood, providing a measure of immune function.
NEUTn	Absolute number of neutrophils in the blood, important in detecting bacterial infections.
RBC	Red Blood Cell count, reflecting the number of red blood cells that carry oxygen throughout the body.
HGB	Hemoglobin level in the blood, indicating the oxygen-carrying capacity of the blood.
HCT	Hematocrit, the proportion of blood volume occupied by red blood cells, used to diagnose anemia.
MCV	Mean Corpuscular Volume, representing the average size of red blood cells, important in anemia classification.
MCH	Mean Corpuscular Hemoglobin, indicating the average amount of hemoglobin per red blood cell.
MCHC	Mean Corpuscular Hemoglobin Concentration, measuring the average concentration of hemoglobin in red blood cells.
PLT	Platelet count, reflecting the number of platelets in the blood, crucial for blood clotting.
PDW	Platelet Distribution Width, measuring the variation in platelet size, which can indicate platelet disorders.
PCT	A procalcitonin test can help your health care provider diagnose if you have sepsis from a bacterial infection or if you have a high risk of developing sepsis.
Diagnosis	The target variable indicating the type of anemia or blood disorder diagnosis.

Machine Learning Models

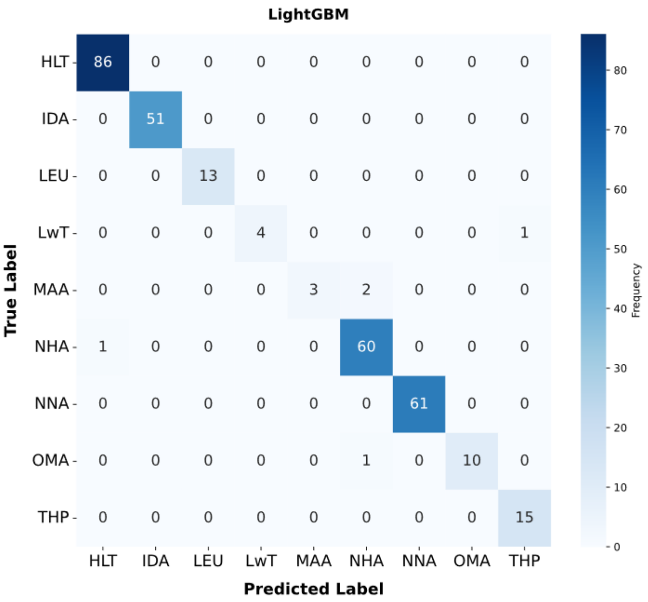
Table 2 describes the ML algorithms employed in this research project, as well as a short explanation of how they work. The algorithms were decided upon with careful consideration for their proven track record in other successful classifying problems and their core mechanisms of capability to deal with complicated, high-dimensional data. All algorithms have unique and inherent strengths that further enable them to wrestle with some of the differences between various types of anemia and blood disorders.

The selection process prioritized factors such as predictive accuracy, computational efficiency, and the model's ability to uncover subtle patterns within the data. By aligning each algorithm's strengths with the study's goals, we aimed to ensure a robust and meaningful classification process. The summarized descriptions in Table 2 highlight how each approach supports the overarching objectives of the research.

Experimental Setup and Evaluation Metrics

Light Gradient Boosting Machine (LightGBM): The LightGBM classifier demonstrated excellent performance in classifying types of anemia, achieving an overall accuracy of 98.38%. The model obtained perfect scores (precision, recall, and F1-score) for certain classes, including Class 1 (Iron deficiency anemia), Class 2 (Leukemia), and Class 6 (Normocytic normochromic anemia).

Although performance was slightly lower for Class 3 (Leukemia with thrombocytopenia) and Class 4 (Macrocytic anemia), with recall rates of 80% and 60% respectively, the overall success remained high. The model's macro F1-score of 0.95 and weighted average F1-score of 0.98 indicate a balanced and stable performance across classes of different sizes. These findings confirm that LightGBM is a highly suitable algorithm for multi-class classification tasks on medical datasets.Table 3 provides a detailed summary of its model performance, and the confusion matrix is shown in Figure 3 for further visual inspection.



	HLT	IDA	LEU	LwT	MAA	NHA	NNA	OMA	THP
HLT	86	0	0	0	0	0	0	0	0
IDA	0	51	0	0	0	0	0	0	0
LEU	0	0	13	0	0	0	0	0	0
LwT	0	0	0	4	0	0	0	0	1
MAA	0	0	0	0	3	2	0	0	0
NHA	1	0	0	0	0	60	0	0	0
NNA	0	0	0	0	0	0	61	0	0
OMA	0	0	0	0	0	1	0	10	0
THP	0	0	0	0	0	0	0	0	15

Figure 3 The Confusion Matrix obtained from the LightGBM algorithm used is shown

Table 2 Algorithms used in the study

Algorithms	Description
Decision Tree (DT)	Decision Trees are straightforward yet effective classification tools that iteratively split the dataset based on feature values to build a tree-like structure. Their main strengths lie in their interpretability and speed, especially for small to mid-sized datasets. However, without pruning or depth control, they risk overfitting Muyama *et al.* (2024); Islam *et al.* (2024); Kasthuri *et al.* (2024).
Random Forest (RF)	Random Forest improves upon individual decision trees by constructing an ensemble of them using random subsets of data and features. This reduces overfitting and enhances generalization, though interpretability can suffer due to the model's complexity Muyama *et al.* (2024); Islam *et al.* (2024).
Gradient Boosting (GB)	Gradient Boosting builds models sequentially, where each new learner focuses on correcting the previous one's errors. While powerful in capturing complex patterns, it may overfit if not properly regularized. Techniques like shrinkage and subsampling help mitigate this issue Mwangi *et al.* (2024).
Extreme Gradient Boosting (XGBoost)	XGBoost is an optimized form of gradient boosting known for its speed, scalability, and high accuracy. It incorporates regularization (L1, L2), second-order optimization, and parallelization, making it highly suitable for large-scale ML tasks Kasthuri *et al.* (2024).
Categorical Boosting (CatBoost)	CatBoost is designed to handle categorical features natively, reducing the need for extensive preprocessing. It employs ordered boosting to avoid overfitting and is efficient both in terms of speed and predictive performance, even on high-cardinality categorical data Mwangi *et al.* (2024).
Light Gradient Boosting Machine (LightGBM)	LightGBM is a gradient boosting framework optimized for speed and memory efficiency. It uses a histogram-based algorithm and leaf-wise tree growth, which accelerates training on large datasets. While faster than many alternatives, it may require careful tuning to avoid overfitting Olatunji *et al.* (2024).

Table 3 Observed data for the LightGBM algorithm

Class	Precision %	Recall %	F1-Score %	Support
0. Healthy (HLT)	99.0	100.0	99.0	86
1. Iron deficiency anemia (IDA)	100.0	100.0	100.0	51
2. Leukemia (LEU)	100.0	100.0	100.0	13
3. Leukemia with thrombocytopenia (LwT)	100.0	80.0	89.0	5
4. Macrocytic anemia (MAA)	100.0	60.0	75.0	5
5. Normocytic hypochromic anemia (NHA)	95.0	98.0	97.0	61
6. Normocytic normochromic anemia (NNA)	100.0	100.0	100.0	61
7. Other microcytic anemia (OMA)	100.0	91.0	95.0	11
8. Thrombocytopenia (THP)	94.0	100.0	97.0	15
Macro avg	99.0	86.0	96.0	308
Weighted avg	98.0	98.0	98.0	308

Feature Importance Analysis

The feature importance visualization in Figure 4 offers a clear picture of which variables the LightGBM model relied on most when making its predictions. Among these, Mean Corpuscular Volume (MCV) emerged as the most influential factor, followed closely by Mean Corpuscular Hemoglobin (MCH) and Hemoglobin (HGB). These features, commonly used in clinical assessments of blood disorders, appear to play a central role in helping the model distinguish between different types of anemia. Features like MCHC, WBC, RBC, and PLT also showed substantial contributions, further supporting the importance of red and white blood cell characteristics in diagnostic classification. In contrast, variables such as PDW, NEUTp, and LYMn had relatively lower importance scores, suggesting they had a more limited effect on the model's decision-making. Taken together, these findings suggest that LightGBM, much like a clinician, places greater weight on core hematological indicators particularly those reflecting red blood cell morphology when interpreting patient data for classification purposes.

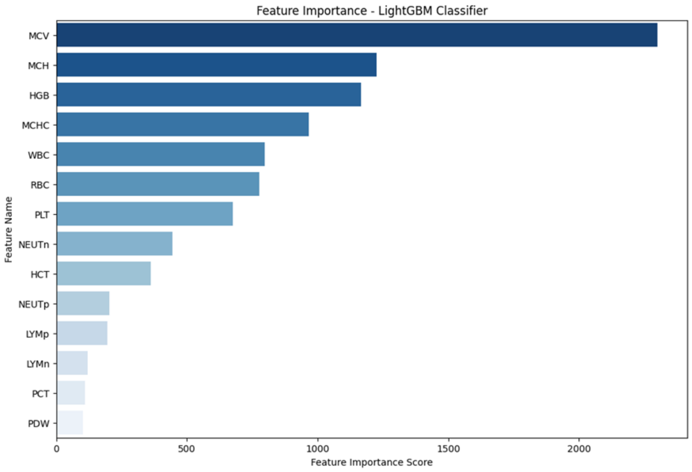


Figure 4 Illustrates the feature importance plot for the LightGBM algorithm, highlighting the relative significance of each feature in the model's classification process

RESULTS AND DISCUSSION

In this section, an independent diagnostic method is provided that employs ML techniques for the diagnosis of anemia, which is a common and clinically significant blood disorder. The study aimed to implement and evaluate several of the most common ML algorithms found in the literature, using data associated with anemia. The results from the experiments performed using these algorithms are summarized in Table 4.

Table 4 The experimental results of the ML algorithms tested on the Anemi dataset

Rank	Models	Accuracy %
1	LightGBM	98.38
2	CatBoostClassifier	98.37
3	Decision Tree	98.05
4	Gradient Boosting	98.05
5	Random Forest	97.72
6	XGradient Boosting	97.72

LightGB ends up as the best performing model with accuracy of 98.38%, demonstrating its powerful capability to not only handle large datasets but also deliver accurate predictions. LightGB is a powerful, fast learner, making it a strong candidate for complex classification problems. CatBoostClassifier follows closely behind at an accuracy of 98.37%, capable of handling categorical features and improving performance using a methodology based on Gradient Boosting. The Decision Tree and Gradient Boosting models were also accurate at 98.05% due to their ability to properly account for feature interactions although Decision Trees can be overly complex in some instances. Random Forest and XGradient Boosting were accurate at 97.72%, but Random Forest lessened overfitting by averaging across many trees.

These models are less competitive than LightGB but will still remain with a strong tree-based model when accounting for feature interactions. The performance of these models is also influenced by things such as feature selection, data preprocessing, and hyperparameter tuning and optimizations. If these criteria were optimized properly, it is likely that the models would do even better with their performance. Another consideration is computational efficiency which is especially vital in real- world applications. LightGB has the best accuracy, but it may demand quite a bit of computational effort when using very large datasets. Random Forest and XGradient Boosting lend themselves much more readily and easily to greater scalability when designing and implementing staged solutions and implementations. In future studies, more focus could be aimed at aspects such as feature engineering, and building hybrid models that incorporate deep learning methods and algorithms, which may lead to increased classification accuracy. Additionally, providing explanations of model outputs using explainability measures, such as SHAP values, or LIME will likely provide some visibility to model outputs that can promote the user trust characteristic that often is missing in AI- based diagnostic systems (Kasthuri *et al.* 2024) .

CONCLUSION

This investigation demonstrates the significant potential of machine learning (ML) models for the early detection and classification of anemia and other blood disorders by conducting a comparative analysis of various algorithms including LightGBM, CatBoost, Decision Tree, Gradient Boosting, Random Forest, and XGBoost using key hematological parameters such as RBC, WBC, HGB, and PLT. The results identified LightGBM and CatBoost as the superior models, achieving high accuracies of 98.38% and 98.37%, respectively, thereby validating their capacity to discern complex patterns within clinical data. The clinical implications of these findings are substantial, as the high diagnostic accuracy offered by these models can facilitate prompt and appropriate treatment planning, a critical factor in managing conditions like anemia. Furthermore, the integration of such validated models into clinical workflows presents an opportunity to reduce diagnostic errors and treatment delays, enhancing healthcare system efficiency.

Building upon this foundation, future research trajectories could focus on refining these algorithms for broader, accessible application across diverse datasets and clinical contexts. While LightGBM and CatBoost excelled in this study, it is acknowledged that other analytic techniques might yield different results depending on the specific data and clinical setting. Directions for future enhancement also include the exploration of more advanced deep learning or hybrid architectures that may offer greater accuracy and a superior capacity for managing complexity. To ensure clinical adoption, the deployment of eXplainable AI (XAI) techniques, such as SHAP or LIME, is imperative to foster the transparency and trust necessary for uptake by healthcare professionals. Ultimately, this work corroborates the escalating influence of ML methods in medical diagnostics and underscores how these sophisticated analytical tools are advancing the paradigm towards precision and personalized healthcare, a vital step in tackling global health challenges related to hematological disorders.

Ethical standard

The author has no relevant financial or non-financial interests to disclose.

Availability of data and material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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