Anemia Detection Using Machine Learning and Deep Learning - A Systematic Literature Review

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ABSTRACT

Anemia is a crucial global public health issue with women and children have high risk of contraction. Anemia is caused due to scarceness of Red Blood Cells also known as RBCs in the body. Diagnosis of Anemia has traditionally been through invasive means by means of drawing blood from the body. Invasive measures cause pain to the body and also not easily accessible to the masses. This study aims to review various Machine learning and deep learning techniques that can be employed for the detection of anemia in a non-invasive manner. Studies of various literature and research papers published on the subject detection of anemia using machine and deep learning were carried out. Non-invasive techniques based on Machine Learning and Deep Learning play a pivotal role in the early detection and treatment of anemia in an efficient and cost-effective way.Using convolutional neural networks (CNN), the proposed model effectively eliminates relevant features from different blood samples. Preprocessed datasets, including blood smears and microscopy images, enable training and validation. The model is highly effective in identifying abnormal blood signatures associated with anemia, helping to make early and accurate diagnosis. Our findings demonstrate the potential of deep learning as an important tool in diagnosing type 2 diabetes, providing better results and saving time compared to other diagnostic methods. The research helps advance clinical image analysis and highlights the importance of artificial intelligence in improving diagnosis.

Keyword - *Anemia Detection, Machine Learning, Deep Learning*

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1. INTRODUCTION

Anemia is an important global health issue. According to the World Health Organization (WHO), anemia is defined as having hemoglobin (Hb) levels below 12.0 g/dL in females and 13.0 g/dL in males [1]. The WHO has recognized iron deficiency anemia (IDA) as the most common nutritional deficiency with around 30% people affected in the world. Although the most common causes of IDA are gastrointestinal bleeding, decreased dietary iron and iron absorption are also culpable causes [2].

Diverse etiologies underlie anemia, with notable instances encompassing Iron and Vitamin deficiency anemia, Haemolytic anemia, Aplastic anemia, Sickle cell anemia, Thalassemia, Chronic diseases, etc. Causes of anemia include nutritional deficiencies, especially iron, vitamin A, B vitamins, folic acid, chronic inflammation, parasitic infections, and congenital conditions [3].

The traditional way of diagnosing anemia is by drawing a blood sample from the patient and analyzing its hemogram. This procedure however is invasive, painful, and difficult to coordinate among pediatric groups.

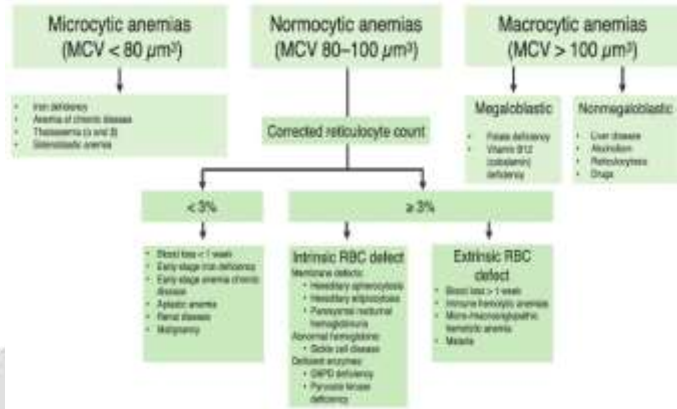


Fig-1:Types of Anemia

To overcome these challenges, a non-invasive approach based on Machine Learning (ML) and Deep Learning (DL) is employed. This approach is cost-effective, takes less time, and is useful for the initial diagnosis of anemia [4].

ML aids anemia detection by analyzing diverse data sets like blood tests and clinical records. ML models recognize patterns from the training data that are then used to classify new data.

ML is generally considered fit for the classification of non-visual data. Ensemble Learning can be employed to leverage several models to improve accuracy.

DL is pivotal in anemia detection by leveraging complex computational models to analyze diverse data sets. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are commonly employed to discern patterns in high-dimensional data, such as medical images or time-series information related to anemia. DL enables for the automatic extraction of intricate features, enhancing the accuracy of anemia detection.

1.1 METHODOLOGY

In conducting this detailed literature review on Anemia Detection using ML and DL, a systematic approach was applied to find and analyze relevant studies. Utilizing databases such as IEEE Xplore, Wiley Online Library, Science Direct, and Google Scholar, a targeted search was carried out focused on key terms related to anemia detection, ML, and DL.

Criteria for the selection of studies which included relevance, language of the study, and publication year, was established to ensure the selection of the most pertinent studies. Following initial title and abstract screening, full-text reviews were carried out to determine the eligibility of studies based on predefined criteria. Upon selection, data extraction was carried out which encompassed extraction anemia detection methods, methodology, statistical techniques, data sets used, and associated findings.

The process employed adheres to a predefined review protocol, emphasizing transparency, replicability, and ethics. Ethical considerations were given due regard, ensuring proper citation and acknowledgment of the original authors. By employing this methodology, the literature review aims to provide a robust and insightful overview of the current algorithms and their performance in anemia detection, contributing to the understanding of advancements and challenges in this critical domain.

2. Lierature Review

ML is the field of computer science that enables computers to learn from data without being explicitly programmed. ML empowers the ability to gain insights from the huge amount of data that is being created daily in an efficient and effective.

DL is a branch of ML based on Artificial Neural Networks (ANNs). It is capable of learning complex patterns and relationships within data. It has seen a meteoric rise in usage due to the advances in processing power and the availability of large data sets. Because it is based on ANNs also known as deep neural networks (DNNs). ANNs are inspired by the structure and function of the human brain's biological neurons, and they are designed to learn from large amounts of data.

Various ML and DL models can be used to detect anemia in a non-invasive fashion, such as Naive Bayes (NB), Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Networks (CNNs), etc.

2.1 Naive Bayes (NB)

NB is a supervised learning algorithm that is based on Bayes' Theorem and assumes conditional independence among features. It is also known as a probabilistic classifier since it uses probability for classification. It faces a "Zero Probability Problem" for unseen events.

Bayes Theorem is given by:

$$P(A|B) = P(B|A) * \frac{P(A)}{P(B)}$$

where P(A|B), P(B|A), P(A) and P(B) are Posterior Probability, Likelihood, Prior Probability and Marginal Probability respectively.

B. A. Patel et al [13], carried out a study on Impact Analysis of Complete Blood Count (CBC) Parameters using the NB algorithm over the CBC data set with an accuracy of 85.12%.

P. Appiahene et al [4], conducted a comparative study on the Detection of Iron deficiency Anemia using ML Algorithms over Fingernail, Palpable palm, and Conjunctiva data sets. On employing the NB algorithm, the yielded accuracy was 94.94%, 94.94%, and 98.96% over Conjunctiva, Fingernail, and Palpable palm data sets respectively.

Turker Berk Donmez et al [6], conducted a study on the Detection of Anemia using Non-invasive Analysis of Lip (mucosa) images. It was found that NB achieved the highest accuracy of 96% among all other algorithms employed. This study also demonstrated that the Lip (mucosa) image can be also used for Non-invasive Anemia detection.

2.2 Support Vector Machine (SVM)

SVM is a supervised learning algorithm that works best on complex and small data sets. It aims at utilizing limited insights in the existing training data to get the best classification results. SVM aims to find the hyperplane that maximizes the margin (distance between the closest points of the distinct classes), that separates the classes in the feature space. The points nearest to the hyperplane are termed support vectors.

The SVM Equations are given by:

Linear SVM:

$$f(x) = w * x + b$$

Non Linear SVM:

$$f(x) = \sum_{h=1}^{n} \alpha_h y_h K(x_h, x) + b$$

where x, w, b, α_h, y_h and K are input feature vector, weight vector, bias, Lagrange multipliers, class label and kernel function respectively.

S. Bauskar et al [5], conducted a study on a Non-invasive computerized Technique to Detect Anemia using Images of the Eye (Conjunctiva). In this study, SVM was found to detect anemia with an accuracy of 90% using Images of Eye (Conjunctiva). The data set used was small containing only 99 instances.

Fig-2: Anemic Eye (Conjunctiva)

Turker Berk Donmez et al [6], conducted a study on Anemia detection through Non-invasive analysis of Lip (mucosa) images. SVM was used to detect Anemia with an accuracy of 75%. The size of the data set was small 138 patients, including 100 women and 38 men.

P. Appiahene et al [4], conducted a comparative study on the Detection of Iron deficiency Anemia using ML Algorithms over Fingernail, Palpable palm, and Conjunctiva data sets. SVM was employed to detect anemia using images of Palpable palms with an accuracy of 90% and yielded the highest accuracy when compared to studies conducted with other medical images such as Eyes (conjunctiva).

C. C. Hortinela et al [7], proposed a system for Identification of Abnormal RBCs and Type of Anemia using SVM. The system developed acquired an accuracy of 93.33% in identifying 7 different Red Blood Cells (RBCs) such as echinocytes, elliptocytes, stomatocytes etc. The data set used was small and contained only 120 instances.

TABLE -1 LITERATURE REVIEWED

Reference	Data set	Algorithms	Accuracy(%)
[4]	Palm Image Samples (size: 527)	CNN KNN DT NB SVM	99.92 99.92 97.32 99.96 94.94
[5]	Eye (Conjunctiva) Image Samples (size: 99)	SVM	93.00
[6]	Lip (Mucosa) Image Samples	ANN DT KNN NB SVM	93.00 93.00 93.00 96.00 75.00
[7]	Red Blood Cell (RBC) Image Samples (size: 120)	SVM	93.33
[9]	Eye (Whole Conjunctiva) Image Samples + Eye (Palpebral Conjunctiva) Image Samples (size: 211)	RUSBoost RF RUSBoost RF	83.00 ± 4.00 84.00 ± 3.00 83.00 ± 4.00 85.00 ± 3.00
[10]	Eye (Palpebral) Image Samples (size: 104)	SVM DT KNN	73.91 82.60 73.91
[11]	Red Blood Cell (RBC) Image Samples	KNN SVM	73.33 83.33

	(size: 80)		
[12]	Complete Blood Count (CBC) Samples (size: 400)	DT	88.88 (Hold out) 86.26 (10 fold cross validation)
[13]	Complete Blood Count (CBC) Samples (size: 2151)	NB	85.12
[14]	Lip (Mucosa) Image Samples (size: 138)	Transfer Learning CNNC	99.28
[15]	Peripheral Blood Image Samples (size: 196)	PCNN-15 PCNN-48 DAPN-48 VGG-19 RESNET-50 (Deep CNN)	99.83 78.67 99.83 97.48 98.83
[16]	Palpable Palm Image Samples (size: 710)	NB SVM ANN DT (Bagging) Boosting RF+SVM+ANN RF+DT+NB SVM+NB+RF ANN+SVM+NB+DT+ RF SVM+ANN+NB (Voting) NB+RF RF+NB+SVM NB+RF+SVM+ANN ANN+DT+RF+SVM+ NB SVM+NB+ANN (Stacking)	79.95 80.48 78.56 79.24 74.67 82.46 99.22 83.16 87.30 82.00 99.98 99.53 99.30 99.98 82.12
[17]	Complete Blood Count Samples (size: 16721)	XGboost Adaboost	100.00 100.00
[18]	Sensor Data Samples (size: unknown)	Meta Model (SVM+DT+KNN+RF)	95.00

2.3 Random Forest (RF)

RF is a popular supervised machine learning algorithm. It is used for both Classification and Regression problems. RF combines multiple trees to perform classification. Some decision trees may yield correct output while others may not, but all trees together always produces a correct result.

RF reduces the risk of overfitting and provides flexibility to handle both classification and regression problems.

The equations governing RF are:

$$Classification:$$

$$\hat{y}(x) = mode\big(y_1(x), \quad y_2(x), \dots, y_n(x)\big)$$

$$Regression:$$

$$\hat{y}(x) = \frac{1}{N}\sum_{h=1}^{N} y_h(x)$$

where $y_h(x)$, x, N are prediction of Tree T_k, input features and total no of Trees respectively.

G. Dimauro et al [9], in their study found RF's accuracy is better than that of RUSBoost, although RUBoost sensitivity is much higher than that of RF. The study was conducted using two data sets containing Whole Conjunctuva and Palpebral Conjunctiva Images. This phenomenon was observed because RUSBoost was designed to treat unbalanced data sets and has shown very high performance in this literature. The data sets used were augmented and contained a total of 211 instances.

2.4 K Nearest Neighbour (KNN)

The KNN algorithm is a popular algorithm used for classification and regression tasks. It is based on the notion that similar data points tend to have similar labels or values. KNN is the most straightforward calculation among all machine learning algorithms. The KNN algorithm stores the entire training data set as a reference during the training phase and uses it to classify new instances. It is also known as Lazy Learner due to its defers learning till classification.

Equations governing KNN are:

$$\text{Classification:}$$

$$\hat{y}(x) = argmax_c \sum_{i=1}^{k} \delta(y_i, c)$$

$$\text{Regression:}$$

$$\hat{y}(x) = \frac{1}{k}\sum_{i=1}^{k} y_i$$

where $\delta(y_i, c)$ is the Kronecker delta function and y_i is the value of i^{th} neighbour

N. B. Noor et al [10], carried out a comparative study between DT, SVM and KNN to predict an Anemic condition over Eye (Palpebral) image data set containing 104 instances. It was found that KNN algorithm yielded an accuracy of 73.91%. It also finds that the prediction of non-anemic yields higher accuracy than predicting anemia.

P. Appiahene et al [4], in their study found the accuracy of classification of Anemia using the KNN algorithm over palpable palm dataset containing 527 instances to be 99.92 %

Fig-3: Anemic Palm

T. S. Chy et al [11], in their study used KNN for the detection of Sickle Cell Anemia with an accuracy of 73.33% over RBC Image data set containing 80 instances. It was found that KNN yields less accuracy than SVM in regards to the data set and methodology used.

2.5 Decision Tree (DT)

DT is a non-parametric, supervised machine learning algorithm used for classification and regression tasks. The DT algorithm characterizes data sets with the use of a tree structure, which is further used in the computation of discrete target-valued functions. The categorization is accomplished by ordering the features of the data set in a tree from some root to the leaf node. The feature which has the highest information gain is assigned the root node while the least occupies the leaf node.

Equations Governing DT are as follows:

$$Classification:$$

$$G(t) = 1 - \sum_{i=1}^{c} p(i|t)^2$$

$$H(t) = - \sum_{i=1}^{c} p(i|t) \log_2 p(i|t)$$

$$IG = Impurity(parent) - \left(\frac{N_{left}}{N_{parent}} * Impurity(left)\right) - \left(\frac{N_{right}}{N_{parent}} * Impurity(right)\right)$$

$$Regression:$$

$$MSE(t) = \frac{1}{N_t} \sum_{i \, \epsilon \, samples \, in \, node \, t} (y_i - \bar{y}_t)^2$$

$$MAE(t) = \frac{1}{N_t} \sum_{i \, \epsilon \, samples \, in \, node \, t} |y_i - median_t|$$

where c, p(i|t), N_{left}, N_{right}, N_{parent}, N_t, y_i, $\bar{y}_t$, $median_t$, G(t), H(t), IG, MSE(t), MAE(t) denote number of classes, proportion of class i samples in node t, number of samples in left and right child nodes and parent node, number of samples in node t, target value for sample i in node t, mean and median target value in node t, Gini impurity, Entropy, Information Gain, Mean Squared and Mean Absolute error respectively.

P. Appiahene et al [4], in their study employed a Decision Tree approach for the classification of anemia and yielded an accuracy of 97.32% over a data set of palpable palm images containing 527 instances.

R. Vohra et al [12], in their study on Multi-class classification algorithms for the diagnosis of anemia in an outpatient clinical setting used a Complete Blood Count data set with 400 instances which was then feature selected. The accuracy of the employed Decision algorithm was measured to be 96.10% and 91.27% for the “hold out” and “10 fold cross validation” experiment methods respectively.

2.6 Convolutional Neural Network (CNN)

CNN is a type of DL neural network architecture commonly used in Computer Vision. Computer vision is a field of Artificial Intelligence that enables a computer to understand and interpret the image or visual data. There are two main parts of the CNN, which are the feature extraction and classification layer. Feature extraction uses distinct descriptions to improve the accuracy of the data to be processed and aims to extract important information from the data. The classification layer, which happens after feature extraction, uses fully connected neurons to transform the data into various dimensions [8].

P. Appiahene et al [4], in their comparative study on detecting Iron-deficiency Anemia employed CNN which yielded an accuracy of 99.92% over the palm image data set containing 527 instances.

M. Mansour et al [14], conducted a study on the Non-invasive detection of Anemia using Lip (mucosa) image data set containing 138 instances, employed image transfer learning convolutional neural networks. The developed model yielded an accuracy of 99.29% and was considered suitable for deployment.

Dada Emmanuel et al [15], conducted a study of the Deep Convolutional Neural Network Model for Detection of Sickle Cell Anaemia using data set of Peripheral Blood Images containing 196 instances. The paper proposes PCNN and DAPN for classifying Red Blood Cells in SCA diagnosis, finding that the fusion of data augmentation and CNN improves accuracy, with 15-layer networks outperforming 48-layer ones. The study suggests deep learning's efficiency in SCA diagnosis with limited resources, advocating for future interdisciplinary research.

2.7 Ensemble Method (EM)

Ensemble learning is a machine learning technique that enhances accuracy and resilience in forecasting by merging predictions from multiple models. It aims to mitigate errors or biases that may exist in individual models by leveraging the collective intelligence of the ensemble.

Equations governing Voting EM is given by:

$$\hat{y}_{ensemble}(x) = \sum_{i=1}^{N} w_i . \hat{y}_i(x)$$

where $\hat{y}_{ensemble}(x)$, $\hat{y}_i(x)$ and w_i denote ensemble predicted class for input x, predicted class of the i^{th} and weight assigned to the i^{th} model .

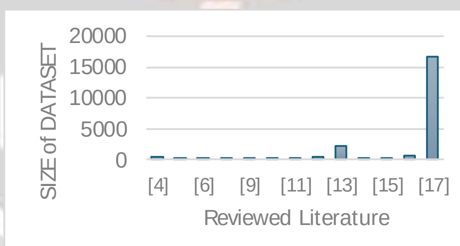
Peter Appiahene et al [16], in their study focused on anemia detection using ensemble models in children. The novel palpable palm data sets containing 710 instances, were used to train and test the models. Stacking, voting, boosting, and bagging ensemble model techniques were used to build the hybrid models, the stacking ensemble model achieved an accuracy of 99.73%. The study justifies that ensemble models are efficient for medical disease diagnosis or detection such as anemia.

Nalluri Schweta et al [17], conducted a study on the Prediction of Anaemia using various Ensemble Learning and Boosting Techniques. In this study various machine learning algorithms were implemented, it was found that the best working algorithms were Adaboost and XGboost with 100% accuracy over the data set formed by combining different data sets from Kaggle containing 16721 Complete Blood Count Samples. Upon evaluation, among the best performers, the execution time was also taken into consideration to determine which classifier works well. Among all the algorithms used, XGboost worked the best with an optimum execution time.

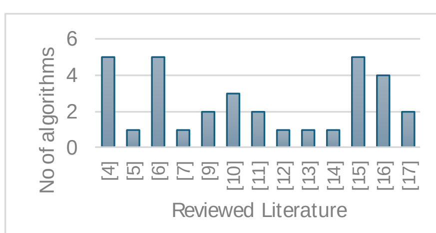
S. Kumar et al [18], conducted a study to develop an intelligent system that utilizes data from sensors and algorithms based on machine learning to optimize fertilizer applications and boost crop yields. It takes the prediction of base models SVM, DT, and KNN as new features, then trains the meta-model which is an RF classifier and makes predictions using the trained meta-model with optimal performance.

2.8 Gaps in Reviewed Literature

On reviewing the above-mentioned works of literature some gaps need to be catered to. In the pieces of literature [5], [6], [7], [9], [10], [11] and [15] the data sets considered by the authors are small and may not represent all possible instances that algorithm might face during real-world applications. The quality and quantity of data sets used determine how useful the model will be to cater to the needs it is developed to cater to.



Studies [5], [7], [12], and [13] only utilize one algorithm which some yield better results and sometimes worse depending upon the data set. To overcome these problems multiple models can be used to train on data sets and then can be coupled used ensemble learning to get the most accurate result.



Furthermore the accuracy of the algorithms in studies [6], [7], [9], [10], [11], [12] and [13] is too low to be considered fit for medical applications where higher accuracy is the utmost need as we are dealing with human lives.

The time complexity of the models developed is not defined in the reviewed study which makes it harder to benchmark them against each other in terms of compute efficiency.

2.9 Limitation of Study

This study is limited in the diversity of study designs and the types of data that are included due to its reliance on published studies. The study's focus is based on the use of medical images for the detection of anemia. Studies or papers that do not meet these criteria for the detection of anemia are not considered and are exempted from this study. This study, in addition, overlooks studies such as pre-print materials or conducted studies outside the scientific community that are not published in a peer-reviewed journal. This is because pre- printed papers or such studies are not indexed or found in the databases searched.

3. CONCLUSIONS

ML and DL have proven to be of great use to detect anemia in a non-invasive and cost-effective way. These algorithms are however not to replace doctors but to assist them in providing affirmative care to patients efficiently and accurately with the repetitive work being handled by the algorithms.

Studies such as [4], [5], [6], [9], [10], [12] [13], [14], [16] and [17] have proved that detection of anemia without invasive procedure is possible and can be done reliably.

While studies like [7], [11], and [15] demonstrate that ML and DL can also be used in the detection of Anemia in invasive samples such as blood if required.

From the reviewed literature it is observed that application of ensemble method combining multiple algorithms (or models) increases accuracy [16], [18] and Convolutional Neural Network consistently yielded acceptable level of accuracy [14], [15] when it was employed. Overall ML and DL have great unexplored potential that can be used in Anemia Care and Healthcare in general.

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