RESEARCH PAPER

Computer-Vision–Based Non-Invasive Detection of Anemia from Medical Images: A Scoping Review of Artificial Intelligence with Applications in Drug Delivery and Therapeutic Monitoring

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ABSTRACT

Anemia is one of the most significant global health concerns, with one-third of the world's population, including children and pregnant women, affected by it." The traditional method of diagnosing anemia involves blood tests, which can be expensive, time-consuming, and challenging, especially for developing countries. Recent developments in artificial intelligence, machine learning, and deep learning have enabled the creation of non-invasive diagnostic tools for detecting anemia, which utilize computer vision for the detection of biomarkers such as the color of tissues such as the conjunctiva, fingernails, palmar tissue, and gingiva, which indicate the presence of pallor, which is associated with hemoglobin deficiency. This scoping review aims to provide an overview of the literature on artificial intelligence-based computer vision for the detection of anemia, which has been conducted between 2017 and 2025. The literature indicates that there is high diagnostic accuracy, which is above 90%, for detecting anemia using convolutional neural networks, support vector machines, and transformer-based models, while image preprocessing plays a significant role in improving the performance of the model.The findings highlight the growing role of computer-vision and machine learning systems in enabling non-invasive screening of anemia through medical image analysis. Computer-based diagnostic platforms that incorporate smartphone imaging technologies may also assist in the development of rapid screening technologies in the community and primary care domains. However, some of the limitations of the current AI-based non-invasive screening technologies include the small datasets, differences in image acquisition conditions, and the lack of external validations in different populations. Despite the limitations, the AI-based non-invasive screening technologies hold significant promise to enhance the detection of anemia in resource-constrained environments..

Keywords: anemia, computer vision, medical images, artificial intelligence

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INTRODUCTION

Anemia is one of the most common blood-related disorders that have become a significant public health concern at the global level. Anemia is characterized by low hemoglobin concentration or the number of red blood cells, resulting in the reduction of the amount of oxygen carried to the tissues. Anemia has become one of the most common blood-related disorders in the world. In fact, anemia affects one out of every three people in the world. Anemia is most common in children below the age of five years and in women of reproductive age. Iron deficiency anemia is the most common type of anemia. Iron deficiency anemia occurs as a result of inadequate iron content in the diet, blood loss, or an increased demand for iron during pregnancy or early development.

The effects of anemia include not only weakness and tiredness. Anemia can cause poor cognitive development in children, poor physical productivity in adults, and maternal and child complications during pregnancy. Anemia should therefore be diagnosed early enough in order to avoid the complications that may result from it. Anemia has commonly been diagnosed using tests that include the complete blood count (CBC), hematocrit, iron tests, and hemoglobin tests.In many low-resource or rural regions, access to such laboratory infrastructure is limited, making

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widespread screening difficult. Additionally, the invasive nature of blood testing may discourage individuals from undergoing routine screening, particularly children or patients with needle phobia. For these reasons, non-invasive screening methods have attracted considerable research interest in recent years.

Clinicians have historically relied on visual indicators such as pallor of the conjunctiva, palm, fingernails, and oral mucosa as preliminary signs of anemia. These tissues are highly vascularized and therefore exhibit visible changes in color when hemoglobin levels decrease. However, visual assessment by clinicians is subjective and often inconsistent, resulting in low sensitivity and specificity.

Recent advances in artificial intelligence and computer vision have created new opportunities for objective analysis of visual biomarkers associated with anemia. Machine learning algorithms can analyze digital images of anatomical regions and identify subtle color variations that correlate with hemoglobin levels. With the widespread availability of smartphones and digital imaging devices, such systems have the potential to provide low-cost screening solutions for anemia in community settings.

Over the last decade, various research studies have been conducted to investigate AI-based methods for anemia detection using conjunctiva, fingernails, palms, sclera, and gingiva image features. The research studies [1-5]have utilized various algorithms, including classical machine learning algorithms like support vector machines and logistic regression, and deep learning algorithms like convolution neural networks and vision transformers.

Considering the rapid development of this field, it is important to have a comprehensive overview of the latest research in this domain to understand the scope, limitations, and potential of AI-based anemia detection methods.

The present scoping study attempts to provide an overview of the latest advancements in non-invasive anemia detection using machine learning algorithms on image features

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2. METHODS

Study Design

This scoping review was conducted to examine the current state of research on artificial intelligence-based non-invasive anemia detection using medical images.

Literature Search Strategy

Relevant literature was identified through electronic databases including PubMed, Google Scholar, IEEE Xplore, and Scopus. The search covered studies published between 2017 and 2025.

The following keywords were used in different combinations:

anemia detection
artificial intelligence
machine learning
deep learning
computer vision
image processing
non-invasive diagnosis

Additional articles were identified by reviewing reference lists of relevant publications.

Inclusion Criteria

Studies were included if they:

Used machine learning or deep learning techniques.
Utilized image-based data (e.g., palm, conjunctiva, nails, gingiva).
Reported performance metrics such as accuracy, sensitivity, specificity, or AUC.
Focused on anemia detection or hemoglobin estimation.

Exclusion Criteria

Studies were excluded if they:

Used only laboratory data without imaging.
Lacked clear evaluation metrics.
Were opinion pieces or editorials.

Data Extraction

Information extracted from each study included:

imaging modality
dataset size
machine learning algorithm
preprocessing techniques
diagnostic performance metrics

The results were synthesized and categorized according to imaging modality and algorithm type.

3. RESULTS

Recent investigations into artificial intelligence–based anemia detection demonstrate a rapidly growing body of research focused on non-invasive diagnostic techniques. These approaches typically rely on analyzing visible anatomical structures whose coloration reflects underlying hemoglobin concentration and tissue perfusion. The most commonly studied regions include the conjunctiva of the eye, the palm, the fingernail beds, the sclera, and the oral mucosa. These tissues contain dense microvascular networks and relatively thin epithelial layers, allowing changes in blood oxygenation and hemoglobin levels to manifest as variations in color intensity. Traditional clinical examinations frequently rely on these visual indicators to identify potential anemia; however, the accuracy of such assessments depends heavily on clinician experience and environmental conditions such as lighting. Computer vision techniques attempt to standardize this process by extracting objective quantitative features from digital images. In many studies, digital photographs were captured using smartphone cameras or clinical imaging devices and subsequently processed through a series of preprocessing steps. These steps commonly included segmentation of the region of interest, removal of background artifacts, illumination correction, and conversion to alternative color spaces such as HSV or CIELab. Such transformations allow algorithms to isolate color channels that correspond to hemoglobin-related redness while minimizing the effects of external lighting conditions. Feature extraction methods often calculate parameters such as the erythema index, red channel intensity, normalized color ratios, or chromaticity values. These features serve as inputs for machine learning algorithms that classify images into anemic or non-anemic categories or estimate hemoglobin levels directly. Palm images are widely used because the palmar surface provides a relatively uniform background with minimal pigmentation variation. Studies using segmentation models such as U-Net have demonstrated accurate extraction of the palm region prior to feature analysis. In pediatric populations, automated palm segmentation followed by color feature extraction has enabled classification models to achieve high predictive accuracy. The conjunctiva remains one of the most extensively studied anatomical regions for anemia detection due to its transparent structure and strong correlation between tissue redness and hemoglobin concentration. In several investigations, conjunctival images were processed to isolate the palpebral conjunctiva, after which color features were extracted and analyzed. Deep learning models trained on conjunctival images have achieved very high classification accuracy, suggesting that the visual appearance of conjunctival tissue provides a reliable indicator of hemoglobin deficiency. Fingernail beds and gingival tissues have also been investigated as alternative imaging sites. Nail beds provide an easily accessible surface where capillary blood flow produces characteristic coloration patterns. Similarly, gingival tissues within the oral cavity are highly vascularized and can reveal subtle pallor associated with anemia. The presence of multiple viable imaging sites indicates that AI-based anemia detection systems may be adaptable to different clinical or community screening environments.

Another major trend observed across the literature is the wide range of machine learning algorithms used to perform anemia classification or hemoglobin estimation. Early research primarily relied on classical machine learning algorithms that require explicit feature extraction prior to classification. Support vector machines, logistic regression, naïve Bayes classifiers, and decision trees are among the most frequently applied algorithms. Support vector machines have been particularly successful due to their ability to identify optimal decision boundaries within high-dimensional feature spaces. When trained on carefully engineered color features derived from anatomical images, SVM classifiers have demonstrated strong performance in distinguishing between anemic and healthy individuals. Random forest models and other ensemble learning techniques have also been widely used because they combine multiple decision trees to improve predictive accuracy and reduce overfitting. Logistic regression models, although mathematically simpler, have shown strong performance in several datasets when appropriate color features are provided. As computational resources and image datasets expanded, deep learning approaches gradually became the dominant method for anemia detection. Convolutional neural networks represent the most commonly applied deep learning architecture due to their ability to automatically learn hierarchical visual features from raw images. CNN models eliminate the need for manual feature engineering and instead identify complex spatial patterns associated with hemoglobin deficiency. Studies applying CNNs to palm images, conjunctival photographs, and fingernail images frequently report diagnostic accuracies exceeding 90 percent. In comparative studies where both classical algorithms and deep learning models were evaluated on the same dataset, CNN architectures consistently demonstrated superior performance. Recently, transformer-based models have also emerged as powerful tools for medical image analysis. Vision Transformers utilize self-attention mechanisms to analyze relationships between distant regions of an image, allowing the model to capture global contextual information rather than relying solely on local convolutional filters. Early applications of transformer architectures in anemia detection have reported extremely high accuracy levels approaching 98 percent when applied to conjunctival and scleral images. Hybrid models combining convolutional feature extraction with classical classifiers such as SVM have also been explored. These systems leverage the feature learning capacity of deep neural networks while maintaining the decision boundary robustness of traditional machine learning algorithms. Overall, the diversity of algorithms applied in this field reflects ongoing efforts to balance predictive accuracy, computational efficiency, and interpretability.

Dataset characteristics and image acquisition conditions also play a critical role in determining model performance. Across the reviewed studies, dataset sizes varied substantially, ranging from fewer than one hundred images to several thousand samples collected from multiple clinical sites. Small dataset sizes remain a common limitation due to the challenges of obtaining labeled medical images linked with confirmed hemoglobin measurements. To address this issue, researchers frequently employ data augmentation techniques such as rotation, flipping, scaling, and brightness adjustment to artificially increase the size of the training dataset. Data augmentation improves model generalization by exposing algorithms to a wider variety of image conditions. Another important factor affecting model accuracy is lighting variation during image capture. Changes in illumination intensity or color temperature can alter the perceived redness of tissues, potentially affecting color-based feature extraction. Many studies address this problem through color normalization techniques or by converting images to alternative color spaces that separate luminance from chromatic components. Skin pigmentation differences across populations also represent an important consideration. Some studies report that models trained on specific populations may perform differently when applied to individuals with different skin tones. Interestingly, several investigations have observed particularly strong predictive performance in populations with darker skin tones when analyzing conjunctival or palmar images, possibly due to increased contrast between normal and anemic coloration. Nevertheless, the majority of existing datasets remain geographically limited, highlighting the need for larger multicenter datasets representing diverse ethnic groups. In addition to binary classification models, several studies have also developed regression models capable of predicting hemoglobin concentration directly from image features. Random forest regression and gradient boosting algorithms have demonstrated strong correlation between predicted and measured hemoglobin values. Such regression models could potentially allow quantitative estimation of hemoglobin levels without invasive blood

testing, although further validation is required before clinical implementation.
Finally, several studies [6-15]emphasize the importance of interpretability and clinical integration of AI-based anemia screening tools. Deep learning models are often criticized for functioning as "black boxes," making it difficult for clinicians to understand how predictions are generated. To address this challenge, researchers have begun incorporating explainable AI techniques such as Grad-CAM visualizations, SHAP values, and attention maps. These methods highlight the specific regions within an image that contribute most strongly to the model's prediction. In anemia detection systems, attention maps frequently emphasize areas of high vascular coloration or regions with reduced redness, confirming that the algorithms rely on physiologically meaningful visual cues. Interpretability techniques therefore improve clinician confidence and facilitate integration of AI tools into medical practice. In parallel with algorithm development, several research groups have proposed smartphone-based applications capable of performing real-time anemia screening. Such systems typically capture an image using the smartphone camera, automatically identify the region of interest, and run a trained machine learning model to estimate anemia risk. These portable tools could significantly improve access to screening in rural communities where laboratory testing is unavailable. Some investigators have also explored combining image-based analysis with other non-invasive sensing technologies such as photoplethysmography to improve diagnostic accuracy. Importantly, most authors emphasize that AI-based screening tools are intended to complement rather than replace laboratory diagnosis. Their primary role would be to identify individuals at high risk for anemia who require confirmatory blood testing. By enabling rapid, low-cost screening of large populations, AI-driven diagnostic systems have the potential to improve early detection and treatment of anemia worldwide. (see tables 1 and 2)
Table 1 : Summary of studies on computer-vision and machine learning–based non-invasive anemia detection using medical images from anatomical sites such as the conjunctiva, palm, fingernails, and gingiva. The table presents the imaging site, dataset size, algorithm used, methodological approach, and reported diagnostic performance

Study	**Year**	**Imaging Site**	**Dataset Size**	**Algorithm**	**Key Method**	**Performance**
Mannino et al.	2018	Fingernail	337 images	CNN	Smartphone imaging	AUC 0.88
Dimauro et al.	2019	Conjunctiva	200 images	ANN	Image color analysis	Accuracy 90%
Peksi et al.	2020	Fingernails	20 images	Naïve Bayes	RGB feature extraction	Accuracy 90%
Verma et al.	2020	Clinical data + image	500 samples	SVM	Hybrid ML model	Accuracy 92%
Chen et al.	2021	Conjunctiva	300 images	CNN	Feature extraction + ML	Accuracy 95%
Yeruva et al.	2021	Conjunctiva	120 images	Decision Tree	Image preprocessing	Accuracy 95%
Mahmud et al.	2022	Lip mucosa	150 images	CNN	Deep learning classification	Accuracy 93%
Appiahene et al.	2022	Palm images	300 images	Random Forest	Color feature extraction	Accuracy 92%
Asare et al.	2023	Palm, nail, conjunctiva	2130 images	CNN	Multi-site comparison	Accuracy 99.1%
Muljono et al.	2024	Conjunctiva	500 images	MobileNetV2 + SVM	Hybrid deep learning	Accuracy 93%
Chatterjee et al.	2024	Gingiva	300 images	Logistic Regression	Intraoral image analysis	AUC 0.85
Navarro-Cabrera et al.	2025	Fingernail	909 images	DenseNet169	Deep CNN	Accuracy 69.8%
Ramos-Soto et al.	2025	Conjunctiva + sclera	1200 images	Vision Transformer	Attention-based explainability	Accuracy 98.47%
Kasiviswanathan et al.	2023	Conjunctiva	400 images	U-Net + CNN	Segmentation + classification	Accuracy 94%

Study	Year	Imaging Site	Dataset Size	Algorithm	Key Method	Performance
Shahzad et al.	2022	Medical images	250 images	Deep CNN	Morphological feature learning	Accuracy 96%
Karagül et al.	2022	Clinical dataset	1000 records	Random Forest	Multivariate prediction	Accuracy 91%
Sarsam et al.	2021	Social media health data	2000 posts	K-means + LDA	Data mining	Accuracy 98%
Collings et al.	2016	Conjunctiva	250 images	Regression model	Erythema index analysis	Sensitivity 85%

Table 2 Summary of machine learning and deep learning algorithms used in anemia detection studies, highlighting their frequency in literature, key advantages, and limitations in medical image analysis.

Algorithm	Frequency-in Literature	Advantages	Limitations
Support-Vector Machine	**Very common**	**Works well with small datasets**	**Requires feature engineering**
Random Forest	**Common**	**Handles nonlinear relationships**	**Less interpretable**
CNN	**Very common**	**Automatic feature extraction**	**Needs larger datasets**
Vision Transformer	**Emerging**	**Captures global relationships**	**Computationally expensive**
Logistic Regression	**Moderate**	**Simple and interpretable**	**Lower performance for complex images**

DISCUSSION

The studies reviewed demonstrate that AI-based image analysis provides a promising alternative for non-invasive anemia screening. The high accuracy achieved by deep learning models indicates that visual biomarkers can serve as reliable indicators of hemoglobin deficiency.

The role of computer-based diagnostic systems in anemia detection can be seen as a significant advancement in digital healthcare and technology-driven strategies. This is because, unlike conventional diagnostic systems, computer vision and machine learning-based diagnostic systems can rapidly process visual biomarkers using portable imaging devices such as smartphones and hand-held cameras. This technological advancement can be seen as a major breakthrough towards a decentralized diagnostic model where anemia risk can be evaluated at the point of care without relying on conventional laboratory diagnostic systems. This can be a significant advancement towards improving the early detection of anemia at primary healthcare centers and community-based healthcare programs. This can be achieved by leveraging computer-assisted image analysis and mobile health technology for data processing and decision-making.Another important implication of computer-based anemia detection systems is their potential integration with digital health ecosystems and telemedicine platforms. Cloud-based computing and mobile applications can allow captured images to be processed either locally or through remote servers, enabling scalable screening programs. In such frameworks, healthcare workers or community health volunteers can capture images of anatomical regions such as the conjunctiva or palm using smartphone cameras, after which computer algorithms automatically estimate hemoglobin levels or classify anemia risk. These systems can generate immediate alerts for patients requiring confirmatory laboratory testing or clinical evaluation. The use of computer-aided diagnostic technologies therefore supports population-level screening initiatives and may play a crucial role in public health programs targeting maternal and childhood anemia, particularly in developing countries where laboratory accessibility remains limited[6--22].

Despite these encouraging findings, several technological and clinical hurdles need to be overcome before computer-based anemia detection systems can be implemented in clinical settings. For instance, variations in conditions for capturing images, such as light intensity, camera quality, and patient pigmentation, may affect algorithmic accuracy and necessitate effective preprocessing strategies. Additionally, existing datasets may be small in size and regional in representation, which could limit the external validity of machine learning models. Future studies should seek to address these issues using large-scale and multi-center datasets. Another important consideration is the integration of computer-based anemia detection systems with existing frameworks of explainable artificial intelligence systems to increase clinician confidence in computer-assisted diagnostic tools. By overcoming these hurdles, experimental models can be translated into reliable clinical tools for supporting anemia control programs globally.

However, several challenges remain:

- limited dataset size
- variability in image acquisition
- lack of external validation
- interpretability of deep learning models

Addressing these issues will be critical for clinical translation.

Future Directions

Future research should focus on:
Large multicenter datasets
Standardized imaging protocols
Explainable AI methods
Integration with smartphone health platforms
Multimodal diagnostic approaches

6. CONCLUSION

AI-based non-invasive anemia detection represents a promising advancement in medical diagnostics. Machine learning algorithms can analyze subtle visual features in anatomical tissues and achieve high diagnostic accuracy. With further validation and technological development, these systems may become valuable tools for large-scale anemia screening programs, particularly in low-resource settings.

Declarations

There are no ethical issues
There is no external financial aid
All the authors have contributed significantly to the article design data collection and manuscript preparation
Both the authors have no conflict of interest.

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