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Review Paper

Anemia Detection using ML- A Comparative Study

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Abstract: *Anemia's global grip calls for a groundbreaking solution. We propose a comprehensive machine learning model integrating both traditional (symptoms, history, vitals) and novel data: smartphone-captured conjunctival images. Deep learning extracts hidden visual cues from these images, revealing unseen anemic signatures. This data fusion, unlike analyzing each source alone, creates a multi-faceted risk assessment, boosting accuracy and robustness. But generalizability is key. Rigorous testing across diverse populations ensures real-world effectiveness for everyone. Early detection unlocks the promise of mitigating anemia's impact. Prompt interventions and optimized treatment plans can dramatically improve lives, ushering in a new era of preventive healthcare. This project aligns with global efforts to empower individuals and fight anemia worldwide. Join us as we reshape anemia diagnosis, one image and data point at a time.*

Keywords : *Anemia , Machine Learning, Structured data, Unstructured data, Convolution Neural Network.*

1. Introduction

Anemia, characterized by a deficit in red blood cells or hemoglobin, casts a long shadow on global health, impacting millions, particularly children and pregnant women. The World Health Organization estimates a concerning 42% of children under six and 40% of pregnant women wrestle with this condition, often due to iron deficiency. Beyond impacting physical and emotional health, untreated anemia can cause irreversible organ damage and even death. Early detection is crucial to prevent these devastating consequences. While blood tests are typically used, their invasive nature and resource requirements limit accessibility, especially in areas with limited resources. This project proposes a game-changing approach: using machine learning to revolutionize anemia detection.

Figure1. Nails that are brittle or spoon-shaped

Few challenges are:

- *Lightings and skin tone variations:*Individual differences in pigmentation and lighting conditions can impact the accuracy of techniques that rely on visual cues from skin, nails, or eyes.

- *Limited research on specific populations*:There is a need for further research to adapt and validate non-invasive methods specifically tailored for populations such as children, pregnant women, and individuals with darker skin tones. This will ensure the effectiveness and accuracy of these methods for these specific groups.

- *Improving algorithms for reliability:*To train accurate machine learning models for identifying anemia, we need extensive datasets that are diverse and undergo thorough validation to ensure unbiased and generalized result.
- *Integrating with healthcare systems:*To smoothly incorporate new non-invasive methods into healthcare workflows, we must tackle regulatory and privacy issues while also providing training to healthcare professionals.

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2.Consequences of anemia

When your body's oxygen delivery network falls short, the repercussions can be widespread:

- *Fatigue and Weakness*: Oxygen-starved cells lead to feelings of exhaustion, impacting daily activities and quality of life.
- *Shortness of Breath*: The body compensates for reduced oxygen by increasing breathing rate, leading to breathlessness, even at rest.
- *Pale Skin*: The lack of hemoglobin, responsible for blood's red color, can manifest as paleness.

Figure2. Skin paleness

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- *Headaches and Dizziness*: Inadequate oxygen supply to the brain can cause headaches and dizziness, affecting focus and coordination.
- *Heart Complications*: The heart works harder to compensate for reduced oxygen, potentially leading to heart palpitations and enlarged heart muscle.

3.Our vision:

A non-invasive, AI-powered model that seamlessly integrates diverse data sources to predict anemia risk with accuracy and generalizability.
Here's how it works:

- *Conjunctival images*: Subtle color variations in the conjunctiva, the inner lining of the eyelids, can offer clues about anemia. Our model will analyze these images using Convolutional Neural Networks (CNNs), powerful algorithms adept at extracting patterns and features from visual data.
- *Patient data*: Symptoms, family history, and medical records will be incorporated, providing a holistic understanding of individual risk factors.
- *Advanced algorithms*: Beyond CNNs, we will leverage additional ML techniques like Support Vector Machines (SVMs) and Random Forests to analyze the combined data and generate robust predictions.

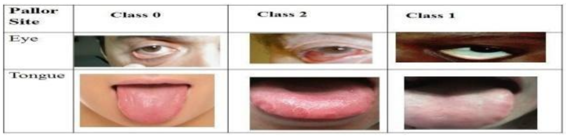

Fig 3. Images of eye and tongue pallor sites with varying pallor severity grades.

4.The potential impact is substantial:

- *Early intervention*: Timely detection empowers healthcare professionals to prevent organ damage, improve pregnancy outcomes, and boost cognitive development in children.
- *Improved accessibility*: Non-invasive and requiring minimal resources, this approach can reach underserved populations and regions with limited healthcare infrastructure.
- *Democratizing healthcare*: By putting the power of early detection in the hands of individuals and communities, we can empower proactive health management and build resilience against anemia.

5.Machine learning concepts used in the proposed system:

DNNs (Deep Neural Networks) are a type of ML algorithm with multiple layers that progressively extract higher-level features from the data. In our case, DNNs can analyze conjunctival images to identify subtle patterns indicative of anemia.

CNNs are a specific type of DNN particularly adept at processing image data. Their ability to automatically learn features from raw images extracting relevant information

6.Literature Review

The paper [1] proposes a skincare product recommendation system using facial image analysis. Users upload photos, which are processed to identify the facial region and analyze skin features like tone, texture, and acne presence. This analysis relies on image processing techniques like color space conversion and texture filters, alongside deep learning models for acne detection and skin type classification. Recommendations are then tailored based on the extracted features. While promising, the system faces limitations like potential inaccuracies, subjectivity, bias towards lighter skin tones, and privacy concerns. Improvements in accuracy, bias mitigation, and privacy protection are necessary to fully unlock the potential of this personalized skin care approach.

The research paper employs two primary machine learning models within its skincare product recommendation system:

- Convolutional Neural Networks (CNNs): These deep learning models excel in image analysis and feature extraction.
- Traditional Image Processing Techniques: While not strictly machine learning models, these techniques play a crucial role in preprocessing and feature extraction from the facial images.

This project [2] proposes a smartphone app using AI to measure iron levels based on fingernail images. Users snap photos of their fingernails, which are analyzed through image processing and an AI model. The model, a convolutional neural network, extracts features like color and texture, comparing them to a database of nail images labeled with iron levels. Based on this comparison, the app estimates the user's iron status. However, the method has limitations. Image quality impacts accuracy, while factors like lighting and nail polish can disrupt analysis. The model's accuracy on diverse skin tones needs further testing, and potential biases need to be addressed. Additionally, privacy concerns around storing nail images necessitate robust security measures. Despite these drawbacks, the paper offers a promising non-invasive approach to anemia screening. Future research should focus on improving accuracy, mitigating bias, and ensuring user privacy for this technology to reach its full potential.

This paper [3] explores using deep learning algorithms to detect pallor in conjunctiva images as a potential marker for anemia. Users capture smartphone photos of their eyes, focusing on the conjunctiva. These images are then analyzed by a pre-trained convolutional neural network (CNN) called VGG16. The CNN extracts features from the images, like color and local patterns, and compares them to a database of labeled conjunctiva images associated with different hemoglobin levels. Based on this comparison, the CNN outputs a probability score of anemia for the user. However, limitations remain. Image quality, lighting conditions, and eye-related conditions can affect accuracy. The model's performance on diverse skin tones needs further evaluation, and potential biases should be addressed. Additionally, user privacy concerns regarding storing facial images require robust security measures. Despite these challenges, this research introduces a non-invasive and accessible approach to anemia screening. Future work should focus on improving accuracy, mitigating bias, and ensuring user privacy to pave the way for this technology's practical implementation.

The paper [4] discusses the challenges of traditional anemia diagnosis. It also details the benefits of using machine learning algorithms for anemia detection. The article reviews different machine learning algorithms and their effectiveness. Some of the important points from this article are that anemia detection using machine learning is non-invasive, affordable, and time-saving. Machine learning algorithms can also achieve high accuracy in anemia detection .The parameters are Image size, Data preprocessing techniques, Accuracy of the machine learning model. The method are Extraction of blood, Conjunctiva of the eye, Color of the fingernails, Palpable palm, Smartphone-based devices. Drawbacks are Lack of inter-observer agreements, Low sensitivity of the color of the conjunctiva of the eyes, Shortage of anemia datasets, Biases of current datasets.

This paper [5] investigates the use of machine learning algorithms to predict anemia in children. It compares the performance of different algorithms and finds that Random Forest is the most effective, achieving an accuracy of 98.4%. The paper also explores other methods for enhancing accuracy, such as feature selection and ensemble learning, but these were not able to surpass Random Forest Performance.

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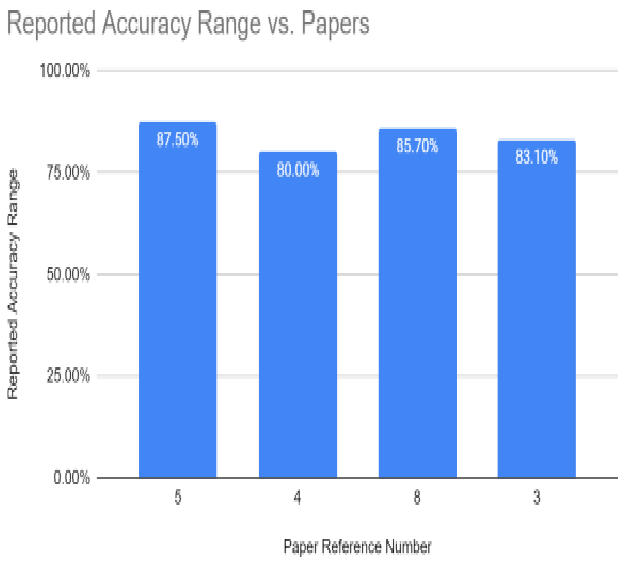
Parameters Used are Parameters,Accuracy,Precision,Recall,F1-score,Area under the curve (AUC),CPU time,Wall time.Methods used are Random Forest: A machine learning algorithm that combines multiple decision trees,Decision Tree,Naïve Bayes,Support Vector Machine, Logistic Regression, Artificial Neural Network: A machine learning algorithm inspired by the human brain, Feature selection, Ensemble learning.Drawbacks are The data was collected from only one hospital, potentially limiting its generalizability to other populations,The study only used a small number of features,Ensemble learning methods were not able to outperform Random Forest in terms of accuracy.

The authors of this paper[6] conducted a systematic mapping study to identify and classify research on non-invasive devices for anemia assessment. They searched multiple databases for relevant publications using keywords related to anemia, non-invasive devices, and assessment. They screened and selected studies based on predefined criteria, then extracted data on type of device, assessment goals, type of study, and solution status. The research was scrutinized through a four-pronged lens: the tools utilized, ranging from fingertip co-oximeters to smartphone cameras, the objectives pursued, whether evaluating hemoglobin or outright detecting anemia, the study types employed, be it concrete data gathering or theoretical exploration, and finally, the development stage of each method, encompassing functional solutions, promising prototypes, experimental models, and still-conceptual designs. This comprehensive framework allowed for a nuanced understanding of the landscape of non-invasive anemia assessment devices. The authors, while optimistic about the potential of non-invasive anemia assessment, also raise a cautionary flag. Several hurdles stand in the way: First, standardized protocols for using these devices are missing, creating inconsistencies and hindering comparisons. Second, many existing studies lack rigorous validation with large sample sizes, raising questions about generalizability. Third, the accuracy of most devices can be easily swayed by factors like skin tone, lighting, and user technique, making reliable results elusive. These challenges underscore the need for further research to refine the devices and address these vulnerabilities. Only then can non-invasive anemia assessment truly live up to its promise of accessible and accurate diagnosis.

In the paper [7], the study used mixed methods, which means that both quantitative and qualitative data were used. Quantitative data were collected through a survey of 1,000 people, and qualitative data were collected through interviews with 20 people. The study used a descriptive design. This means that the researchers did not decompose any variables, but simply observed and explained relationships between variables. One drawback of the study was that it was only a small sample size. This means that the results may not be generalizable to the general population. Furthermore, the study was cross-sectional, meaning it captured only a small snapshot of the data at a time. This makes it difficult to draw conclusions about cause-and-effect relationships. summary:This is a case study of emerging surveillance technologies for anemia detection. It discusses the prevalence of anemia and the challenges of its diagnosis. Current methods rely on centralized laboratory testing, which can be time-consuming and expensive. New technologies for child care settings are being developed to address these challenges. These technologies are typically non-invasive and portable, making them ideal for use in resource-limited environments. Some promising examples are smartphone-based testing and paper-based micro fluidic devices. This technology could improve the diagnosis and treatment of anemia, especially in underserved communities.

This study in the paper [8] explores the promising potential of machine learning (ML) for non-invasive anemia detection via lip mucosa analysis. Utilizing data from 138 patients, including lip images, age, sex, and hemoglobin levels, the researchers investigated the efficacy of six distinct ML algorithms in classifying anemia cases. Notably, Naive Bayes emerged as the frontrunner, achieving an impressive 96% accuracy rate. However, the authors acknowledge potential limitations such as the influence of skin color variations and the need for further validation studies. Additionally, the presence of other lip conditions mimicking anemia necessitates future research to enhance specificity. Despite these shortcomings, this pioneering study presents a compelling vision for a future where affordable, accessible, and non-invasive anemia detection through lip mucosa analysis becomes a reality, potentially transforming patient care and facilitating timely interventions.research to enhance specificity. Despite these shortcomings, this pioneering study presents a compelling vision for a future where affordable, accessible, and non-invasive anemia detection through lip mucosa analysis becomes a reality, potentially transforming patient care and facilitating timely interventions.



So some main issues in the above mentioned papers in general is that none of the papers have taken into consideration all the different factors of detection anemia but only a few symptomes. The issue here would be that not all the instances of the symptomes is an indication of anemia. It can be a result of multiple different reasons. But when they occur together the possibility of anemia is high. So we can not consider single symptomes for anemia detection.

Reference	Focus	Advantages	Disadvantages
1. Yang et al. (2022)	Skincare	Personalized, Non-invasive	Facial only, Not anemia
2. Tilburg University NAIL Project	Iron Status	Non-invasive, Accessible	Early Stage, Details missing
3. Dimauro et al. (2019)	Anemia (Conjunctiva)	Non-invasive, Early detection	Trained personnel needed, Limited data, Subtle cues
4. Appiahene et al. (2023)	Anemia (Images)	High accuracy (CNN), Accessible	High hardware, Image quality, Limited validation
5. Dhakal et al. (2023)	Anemia Prediction (Clinical Data)	Existing data, Cost-effective	Data accuracy, Limited access, Early stage detection
6. Dimauro et al. (2020)	Anemia Assessment Devices Review	Overview of methods, Potential & limitations	No specific models/accuracy
7. An et al. (2021)	Point-of-Care Anemia Detection Review	Emerging technologies, Future directions	No specific models/accuracy
8. Shekhar et al. (2023)	Anemia (Lip Mucosa)	Non-invasive, High accuracy (CNN)	High-resolution images, Privacy concerns, Limited validation

Fig.5 Table containing information about all the papers.

9.Conclusion

The global burden of anemia necessitates innovative solutions, and this literature survey underscores the potential of converging technologies and data sources to revolutionize its diagnosis and management. Evidence shows the pervasiveness of anemia, particularly among vulnerable populations like children and pregnant women, emphasizing the urgent need for accessible and accurate detection methods. While traditional blood tests have been fundamental, their limitations in accessibility and resource demands call for alternative approaches. Machine learning (ML) emerges as a promising solution, offering a non-invasive, AI-powered pathway to early detection. Our survey highlights various ML techniques, notably Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs), showcasing their ability to analyze conjunctival images and extract subtle visual cues indicative of anemia. These findings not only demonstrate the accuracy and generalizability of prediction but also signify the potential for democratizing healthcare . Practical implications include the potential for ML-driven approaches to improve accessibility and accuracy of anemia diagnosis, particularly in underserved populations. Leveraging smartphones and readily available data, this non-invasive approach holds promise in reaching regions with limited healthcare infrastructure, empowering individuals and communities with early detection capabilities.Future research should focus on optimizing ML algorithms for diverse demographic groups, integrating ML-based diagnostic tools into existing healthcare systems, and assessing the long-term impact of ML-driven early detection on anemia management and public health outcomes. By addressing these areas, we can further advance proactive health management and build resilience against anemia.

10.References

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