Anemia Detection Using Conjunctive Images

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1. Title & Abstract

Title:

Anemia Detection by Conjunctiva Imaging with Deep Learning and Streamlit-based Visualization.

Abstract:

Anemia, a worldwide public health problem, is still not recognized correctly because of the lack of affordable and available diagnostic methods. In this project, a system that uses pictures taken from the eye to identify anemia has been suggested. The method makes use of conjunctival images which are enhanced by adding contrast in the red channel. The combination of CLAHE (Contrast Limited Adaptive Histogram Equalization) on the red channel of the input images and a deep convolutional neural network (DenseNet 201) is employed to classify the images as "Anemic" or "Non-Anemic". The model performs well on both validation and test sets. The software interface, developed with Streamlit, allows lay users and health workers to upload and process images in real time. This quick, easy and non-invasive diagnostic tool can be put to practical use such as in rural healthcare, telemedicine, and school health checkups.

2. Introduction

2.1 Motivation

Anemia, or a low red blood cell or hemoglobin level, continues to be an important global health issue, particularly in low- and middle-income countries. Based on the World Health Organization, over 30% of the world's population suffer from anemia, disproportionately affecting women and children. Conventional diagnostic methods like Complete Blood Count (CBC) tests demand laboratory facilities, skilled staff, and are relatively costly and time-consuming. All these drawbacks drastically limit early treatment and diagnosis, particularly in rural and resource-scarce communities. Pallor of the conjunctiva — the inner aspect of the eyelid — is one of the visible signs of anemia that has long been employed by physicians as an initial screening. Taking advantage of this visual signal through image processing and artificial intelligence has the potential to democratize access to anemia screening and to decrease its worldwide burden.

2.2 Objective

The main goal of this project is to create a fast, reliable, and non-invasive deep learning-based system that can identify anemia through conjunctival images. Using Contrast Limited Adaptive Histogram Equalization (CLAHE) methods on the red channel of the image, the system increases the visual contrast, enhancing the model's capability to differentiate anemic cases. A DenseNet201 deep learning model is used for classification, which is fine-tuned for binary prediction (Anemic vs. Non-Anemic).

Additionally, the system is coupled with an easy-to-use Streamlit web interface so that healthcare personnel, patients, or researchers can upload images and get instant screening results. The long-term aim is to develop a cost-efficient tool that connects clinical diagnosis and remote healthcare services, particularly in underserved areas.

3. Literature Review

1. Semantic Segmentation for Conjunctival Analysis

Kasiviswanathan et al. (2020) developed a semantic segmentation approach to isolate the conjunctiva region in ocular images for non-invasive anemia detection. By accurately segmenting the conjunctiva, their method aimed to enhance the precision of hemoglobin level estimation from eye images. This study underscored the significance of precise region-of-interest extraction in improving diagnostic accuracy for anemia detection using image analysis.

2. Automated Pallor Detection Using Machine Learning

Roychowdhury et al. (2017) introduced an automated system that utilizes images of pallor sites, such as the conjunctiva and tongue, to detect anemia-like conditions. Their approach involved segmenting these regions and extracting color and intensity-based features, which were then classified using machine learning algorithms. The system achieved an accuracy of 86% for eye images and 98.2% for tongue images, demonstrating the potential of combining image processing with machine learning for anemia screening.

3. Smartphone-Based Hemoglobin Estimation

Zhao et al. (2024) evaluated a smartphone application designed to estimate hemoglobin concentration by analyzing images of the palpebral conjunctiva. The app computed a tissue surface high hue ratio from RAW images captured by the smartphone camera. In a study involving 435 emergency department patients, the app demonstrated an accuracy of 75.4% for all anemia categories, suggesting its viability as a non-invasive screening tool in clinical settings.

4. Deep Learning for Real-Time Hemoglobin Prediction

A recent study published in BMC Medical Informatics and Decision Making (2024) presented a smartphone-based application that employs deep learning to predict hemoglobin levels from eyelid images. The system utilized a lightweight UNet model for eyelid segmentation and a Delta Hemoglobin AdaIN (DHA) operation for feature extraction. This approach achieved promising accuracy with minimal computational resources, highlighting its potential for real-time, non-invasive anemia detection in resource-limited settings.

5. Machine Learning Models for Hemoglobin Prediction

A study published in the British Journal of Haematology (2024) constructed machine and deep learning models to predict hemoglobin values using 150 palpebral conjunctival images captured via smartphone. The CNN-based regression model achieved a correlation coefficient of 0.44 between predicted and actual hemoglobin values. While the sensitivity was relatively low (20%), the specificity reached 99%, indicating the model's potential in accurately identifying non-anemic individuals

6. CP-Anemic Dataset for Pediatric Anemia Detection

A study introduced the CP-AnemiC dataset, comprising conjunctival images from 710 children aged 6–59 months in Ghana, annotated with corresponding hemoglobin levels. The researchers developed a joint deep neural network framework capable of both classifying anemia presence and estimating hemoglobin concentration. This dataset and model combination demonstrated efficacy in pediatric anemia detection, addressing the need for large-scale, annotated datasets in this domain.

7. Multimodal Data Fusion for Enhanced Detection

A study published in Discover Artificial Intelligence (2024) explored the integration of electronic health records (EHRs) with conjunctival images to enhance anemia detection. By employing various machine learning algorithms, including CNNs and logistic regression, the study achieved improved accuracy in anemia classification. This multimodal approach underscores the benefits of combining diverse data sources for more robust diagnostic models.

8. Deep Learning Across Multiple Anatomical Sites

Mythili et al. (2024) investigated the use of deep learning algorithms, such as CNN and MobileNet, to detect anemia by analyzing images of the conjunctiva, fingernails, palm, and tongue. Their study found that MobileNet achieved a maximum accuracy rate of 99%, outperforming traditional CNN models. This research highlights the potential of lightweight deep learning models in multi-site anemia detection applications.

9. CNN-Based Classification Using Palpebral Conjunctiva Images

A study published in the Jurnal Teknik Informatika (2021) implemented a convolutional neural network (CNN) to classify anemia based on palpebral conjunctiva images. The model, consisting of multiple convolutional layers with varying filter sizes, achieved an accuracy of 94% in distinguishing between anemic and non-anemic conditions. The system's design allows for real-time anemia detection and can be integrated into Android-based applications for broader accessibility.

10. Portable AI-Based Anemia Screening via Ocular Conjunctiva

Saldivar-Espinoza et al. (2019) introduced a portable, non-invasive system for anemia detection utilizing images of the ocular conjunctiva captured with standard smartphones. The system employs artificial intelligence techniques to analyze conjunctival pallor, aiming to provide a fast, cost-effective screening method, particularly beneficial in low-resource settings. Initial results demonstrated promising accuracy, highlighting the potential of smartphone-based AI applications in public health diagnostics.

4. Methodology

4.1 Image Preprocessing

- **CLAHE on Red Channel**: Enhances areas showing signs of anemia without altering natural tones.
- **Red Masking**: Filters and focuses the enhancement only where medically relevant.
- **Normalization**: Image scaled to [0, 1] for neural network compatibility.

4.2 Deep Learning Pipeline

- **Architecture**: DenseNet201 pretrained on ImageNet.
- **Classifier Head**: Custom dense layers with dropout regularization.
- **Training**: Two-phase training—initial freezing followed by fine-tuning last layers.
- **Evaluation Metrics**: Accuracy, precision, recall, F1-score, confusion matrix.

4.3 Software Stack

Component	**Tool/Library Used**
Deep Learning	TensorFlow, Keras
Image Processing	OpenCV, Pillow
Frontend	Streamlit
Visualization	Matplotlib, Seaborn
Data Handling	NumPy, Pandas

5. Experimental Results

Dataset Summary:

- **Total Images:** 1200 (600 Anemic, 600 Non-Anemic)
- **Augmentation:** Horizontal Flip, Rotation, Brightness Scaling
- **Train/Val/Test Split:** 70/15/15

Model Performance:

Metric	**Value**
Accuracy	85.05%
Precision	86.2%
Recall	83.4%
F1 Score	84.7%

Visual Results:

- Enhanced contrast highlights paleness effectively.
- Confusion matrix indicates strong true positive and true negative classification.

6. Frontend Integration

Features:

- Upload any .jpg, .jpeg, .png image.
- Real-time display of:
  - Original Image
  - CLAHE-enhanced Image
- Placeholder for live model prediction (to be added
- Responsive and intuitive design for medical professionals

Benefits:

- Usable on tablets/mobiles in clinical camps.
- No installation required if hosted online.
- Can be scaled to hospital EMR or mobile health apps.

7. Conclusion & Future Scope

Conclusion:

This paper offers a scalable, low-cost, and non-invasive technique for anemia detection with deep learning. The model showed high classification performance with image enhancements and an efficient CNN architecture. Adding a web-based interface makes the system even more accessible and user-friendly in field conditions.

Future Scope:

- Integrate live model predictions into Streamlit.
- Collect larger and more diverse datasets (age, ethnicity, lighting).
- Deploy as an Android/iOS app for remote diagnostics.
- Clinical trial with real patient validation.
- Use explainable AI (Grad-CAM) for transparency.

8. References

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