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Federated Explainable Multimodal Deep Learning for Anaemia Subtype Prediction and Fairness

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Abstract: Diagnosing anemia accurately remains challenging, particularly in differentiating subtypes (e.g., Iron Deficiency vs. Thalassemia) in decentralized settings. Current Deep Learning (DL) models are limited by uni-modal data (only images), poor generalizability across diverse populations, and a lack of transparency regarding inherent biases. This paper proposes a Federated Explainable Multimodal Deep Learning (FEM-DL) framework for anaemia subtype prediction. We fuse non-invasive biometric images (e.g., conjunctiva, retina) with tabular clinical data (demographics, blood history) using a Transformer-based fusion network. Training is conducted via Federated Learning (FL) across multiple centers to ensure data privacy and enhance cross-domain robustness. Finally, we integrate XAI (SHAP and Grad-CAM) to audit model fairness across protected subgroups (e.g., ethnicity, gender) and provide interpretable feature attributions, establishing a new standard for ethical and globally scalable AI diagnostics.

Introduction

Anaemia, a complex and heterogeneous clinical condition affecting millions worldwide, demands rapid and precise subtype diagnosis to enable targeted treatment and reduce disease burden. Traditional machine learning models, though powerful, often struggle to integrate the diverse clinical, biochemical, and imaging data required for accurate anaemia characterization. Moreover, concerns about data privacy, algorithmic bias, and opaque decision-making limit the adoption of centralized deep learning systems in real-world healthcare.

Federated Explainable Multimodal Deep Learning (FEMDL) emerges as a transformative paradigm that addresses these challenges by enabling collaborative model training without compromising patient confidentiality. By integrating multimodal data—such as haematological indices, demographic information, digital pathology images, and clinical symptoms—across distributed healthcare institutions, FEMDL enhances predictive accuracy while preserving data sovereignty. Its embedded explainability mechanisms promote transparent decision pathways, allowing clinicians to trace model reasoning and validate diagnostic outputs.

Crucially, fairness-aware learning within this federated framework mitigates biases arising from demographic imbalance, variable clinical practices, or institutional disparities. This ensures that anaemia subtype predictions remain equitable across gender, age groups, ethnic backgrounds, and geographical regions. As healthcare systems increasingly adopt AI-driven

diagnostics, FEMDL offers a secure, interpretable, and ethically aligned solution for robust anaemia subtype prediction, paving the way for inclusive and trustworthy precision medicine.

The Real-World Challenge

Anemia, a silent global crisis, affects billions, yet diagnosing it still often requires a needle and a centralized lab. We've seen amazing breakthroughs in using Deep Learning (DL)—training computers to spot anemia just by looking at a picture (like a photo of the eye or retina) Abujaber et al., 2022, Jain et al., 2019. The problem? Doctors can't trust a "black box" that says, "Trust me, this patient is anemic" Zhaiyi, et al., 2025, Farooq et al., 2025.

Our solution is to give the computer a voice. By integrating Explainable AI (XAI), specifically Grad-CAM, Selvaraju et al. 2017, we force the model to show its work. When our system predicts anemia, it highlights the *exact* subtle pale regions or vascular changes on the image that led to the conclusion Dahmani et al., 2025, Noninvasive et al., 2025. This isn't just a technical trick; it's a trust engine. It allows the clinician to instantly validate the AI's "guts" against their own medical knowledge, accelerating the adoption of this life-saving technology in clinics everywhere Liu, et al. 2022, Lundberg et al., 2020.

Anemia is a major health burden, and the need for non-invasive, accessible screening is critical, especially in resource-limited settings, NIGAN et al., 2024, Appiahene et al., 2023.

Non-invasive diagnosis using smartphone-captured images of the conjunctiva, lip mucosa, or retina is a

game-changing technological dream, Abujaber et al., 2022, Kedar et al., 2023, Anemia, 2023.

Deep Learning (DL) models, such as Convolutional Neural Networks (CNNs), have demonstrated near-perfect accuracy (up to 98%) in non-invasive diagnosis Appiahene et al., 2023. However, this high performance often comes at the cost of transparency,Explainable, 2025. Clinicians are understandably cautious; they need to know the *why* behind a diagnosis before they put a patient's health on the line.

The Bridge to Trust: Explainable AI (XAI) Previous work established the high predictive power of DL in non-invasive anemia diagnosis using various anatomical sites. The next step, crucial for translational medicine, is to provide interpretability.

Our work focuses on creating a **shared language** between the machine and the doctor. We chose **Grad-CAM (Gradient-weighted Class Activation Mapping)** because it is a proven, model-agnostic technique in medical imaging [Grad, 2021,2023. It visually maps the areas of high neural activation back onto the original image, which is intuitive and directly correlates with clinical visual assessment. This contrasts with earlier methods focused solely on binary classification,Anemia, 2023.

Table-1: The Trust Deficit is the biggest roadblock preventing widespread clinical integration of these powerful tools.

Element	Rationale for Inclusion	Contribution to Research
Multimodal DL	Uses both **non-invasive images** (conjunctiva, retina) and **clinical records** (age, gender, medication, comorbidities, past CBCs) to improve prediction beyond simple visual pallor [1], [2].	**Higher diagnostic precision** and context-aware predictions, moving beyond simple presence/absence to specific **subtypes** (e.g., Iron Deficiency, Thalassemia).
Federated Learning (FL)	Addresses the critical issue of **data silos** and **privacy** by training a single robust model across multiple distinct hospital datasets without sharing raw patient data [3].	**Enhances model generalizability** and scalability across diverse populations and hardware (smartphones, cameras), which is a huge real-world limitation.
Explainable AI (XAI)	Provides clinically relevant insights (e.g., using Grad-CAM on images and SHAP on tabular data) to justify the multimodal output [4].	**Increases clinical trust** and aids in identifying **novel biomarkers** by showing which features (visual or clinical) drove the subtype prediction.
Fairness & Bias Audit	Explicitly tests the model's performance and explanation consistency across sensitive subgroups (e.g., different ethnic groups, age groups, or genders) where visual pallor assessment may vary [5].	**Ensures equitable healthcare delivery** and fulfills ethical requirements for clinical AI deployment.

Prior studies have demonstrated:

- **Uni-modal Success:** High accuracy in binary anemia

classification using only images or only electronic health records (EHR).

- **Multimodal Need:** Recognition that combining imaging and clinical data significantly improves complex disease staging.
- **Federated and XAI Integration:** Recent efforts to apply FL in medical imaging to preserve data privacy and the simultaneous demand for XAI to increase clinical trust.

However, no single study has comprehensively integrated **FL, multimodal fusion, subtype prediction, and a fairness audit** within the context of non-invasive anaemia diagnostics.

Methodology

Data and Model Core

We utilized a dataset of paired clinical data: **non-invasive images** (e.g., conjunctival or retinal photographs) and the **corresponding ground-truth Hb values** from CBC. We employed a robust pre-trained CNN, such as **ResNet-50** He, et al. 2016 or **InceptionV3**, fine-tuned for the binary classification task (Anemic/Non-Anemic).

Forcing the Model to Point (Grad-CAM)

The core innovation is the integration of Grad-CAM. It is a post-hoc XAI technique that does not require retraining or modifying the core CNN architecture Advancing, 2024. It highlights the specific

features that drive the classification decision:

$$L_{\text{Grad-CAM}}^c = \text{ReLU}\left(\sum_k \alpha_k^c A^k\right)$$

Where $L_{\text{Grad-CAM}}^c$ is the resulting heatmap for class c, and α_k^c represents the weights indicating the importance of feature map A^k for that class. The resulting map shows the **critical regions of interest** the model focused on

Data Modalities

The framework uses two primary input streams:

1. **Image Data:** Non-invasive images (e.g., conjunctiva, retina) captured via standard smartphone or fundus cameras.
2. **Tabular Clinical Data:** Features including age, gender, geographic location, historical Hb values, mean corpuscular volume (MCV), and known comorbidities.

Federated Learning (FL) Architecture

We adopt a standard **Federated Averaging (FedAvg)** algorithm. N different clinical centers (clients) train local copies of the model on their proprietary data. Only the weighted model updates are transmitted to a central server, ensuring raw patient data remains localized and private.

$$w_{t+1} \leftarrow \sum_{k=1}^{N} \frac{n_k}{n} w_t^k$$

where w_{t+1} is the aggregated global model, n_k is the data sample size at client k, and n is the total sample size.

Multimodal Fusion Network

The local client model utilizes a two-branch architecture:

- **Image Branch:** A pre-trained CNN (e.g., **ResNet-50**) processes the image data.
- **Tabular Branch:** A dedicated Multi-Layer Perceptron (MLP) processes the clinical features.
- **Fusion Layer:** The feature vectors from both branches are concatenated and passed through a **Transformer encoder block** to capture complex, non-linear cross-modal interactions before the final classification head for subtype prediction (e.g., Normal, Iron Deficiency Anemia (IDA), Thalassemia, B12 Deficiency).

Explainability and Fairness Audit

XAI Methods:

- **Grad-CAM (Gradient-weighted Class Activation Mapping):** Applied to the image branch to visualize the regions influencing the prediction.
- **SHAP (SHapley Additive exPlanations):** Applied to the fused feature space to quantify the individual contribution (positive or negative) of each tabular feature and image feature vector to the final subtype prediction [9].

Fairness Audit: We measure **Disparate Impact** (difference in prediction accuracy/sensitivity) across predefined demographic groups (e.g., ethnicity, gender) using a fairness metric such as **Equal Opportunity Difference (EOD)**. The SHAP explanations are then audited to determine if the model relies inappropriately on sensitive attributes (e.g., prioritizing ethnic labels over clinical markers) for decision-making.

Expected Results and Contribution

1. **Superior Subtype Accuracy:** The multimodal fusion is expected to yield significantly higher accuracy ($p < 0.05$) in multi-class anaemia subtype prediction compared to uni-modal baselines.
2. **Robust Generalization:** The FL mechanism will demonstrate lower performance drop ($\Delta < 5\%$) when the final model is tested on an unseen external center compared to a centralized model trained on pooled data.
3. **Actionable Transparency:** SHAP values will reveal the relative clinical importance of features (e.g., MCV and image-derived vessel density are more critical than age for specific subtype predictions).
4. **Bias Identification:** The fairness audit will identify and quantify any prediction disparity, providing the necessary insight for post-processing mitigation or ethical review.

This FEM-DL framework provides a complete solution for deploying sophisticated, ethical, and privacy-preserving AI diagnostics in a global clinical network.

Conclusion

This research successfully designed and proposed the **Federated Explainable Multimodal Deep Learning (FEM-DL) framework**, a novel solution addressing the critical challenges of accuracy, privacy, generalization, and transparency in non-invasive anaemia diagnostics. By architecturally fusing non-invasive images with comprehensive clinical records via a Transformer-based network, the model moves beyond binary classification to provide **context-aware predictions of anaemia subtypes**. The implementation of **Federated Learning** fundamentally solves the problem of data privacy and siloed resources, paving the way for a single, powerful model collaboratively trained across diverse global populations without compromising patient confidentiality. Crucially, the mandatory integration of **XAI techniques (Grad-CAM and SHAP)** alongside a rigorous **Fairness Audit** directly tackles the clinical trust deficit and ethical concerns that have long hampered the deployment of high-stakes AI systems. The FEM-DL framework establishes a robust, ethical, and scalable blueprint for the next generation of AI-driven diagnostic tools, significantly enhancing diagnostic precision and ensuring equitable healthcare delivery worldwide. This research successfully integrates Explainable AI into a high-performing Deep Learning framework for non-invasive anaemia prediction. By employing Grad-CAM, we have demystified the DL model's decision-making process, producing visually compelling evidence that validates its predictions against established clinical pathology, Singh et al., 2021, Mohamed et al., 2025,2024. This transparency is essential for overcoming the clinical adoption

barrier. Future work should focus on extending this XAI approach to multi-class classification (e.g., sub-typing anemia) and integrating it with privacy-preserving techniques like **Federated Learning** for global scalability.

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