RESEARCH PAPER

Short Title: Anemia Fusion Net for Multimodal Anemia Detection Anemia Fusion Net: A Next-Generation Transformer Architecture for Anemia Detection

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Abstract:
In India, Anemia continues to be a major public health concern, but current diagnostic factors are often based only on individual clinical or demographic markers and leave out the multidimensional variables that determine the situation. This research proposes an AnemiaFusionNet transformer-based framework that employs Text based clinical features, conjunctival image measure, and geospatial data to optimize performance of anemia detection. Clinical or textual data and geospatial information were taken from the National Family Health Survey (NFHS), whereas imagery data composed of piloted palpebral conjunctival images. The conjunctival image set was examined through convolutional encoders and reviewed alongside NFHS-based clinical and locational specifications to enable rigorous multimodal modeling. Firstly, we determined the individual modality models to acquire baseline performance, next we fused the heterogeneous embeddings using a cross-attention transformer section. The fused model constantly surpassed outcomes from unimodal techniques, with performance improvements and improved generalization to subgroups of the population. Spatial representations derived from the integrated model shows persistent high-risk areas across central and eastern part of India. The results underscore the complementary predictive value of visual, clinical, and locational cues, and demonstrate that multimodal learning provides a more detailed and operationally effective approach for early anemia detection and geographically intended public health intervention planning.
Keywords: NFHS Data, AnemiaFusionNet, Transformer Architecture, Deep Learning, Cross-Modal Fusion, Machine Learning
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1. Introduction:

Anemia, which has multiple causes and risk factors including dietary habits, infectious disease, reproductive health practices, and various forms of structural socio-economic inequality, is a highly heterogeneous condition with considerable variation among population groups and geographic regions[1]. Large-scale epidemiologic studies and machine learning studies demonstrate the multifactorial nature of anemia and the association between anemia and certain demographic/socioeconomic factors[2,3]. Models of the association of anemia with demographic/socioeconomic factors created through National Health Surveys highlight that dietary patterning, household characteristics and access to health care resources are important predictors of the prevalence of anemia [4,5].

Spatial and spatio-temporal analyses demonstrate large disparities in the burden of anemia across geographic areas, especially within lower-resourced areas[6–8]. Even though hemoglobin testing represents the gold standard for diagnosing anemia clinically, lack of routine access for routine screening, particularly in rural lower-resourced environments, inhibits timely identification and treatment [9,10]. Therefore, recent research has focused on identifying scalable and data-driven methods for detecting anemia risk independent of laboratory testing [11]. Taken collectively, these studies demonstrate the need for analytical frameworks that account for the multi-dimensionality of

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anemia's influence by capturing the clinical, socioeconomic and contextual science related to anemia.

2. Literature Review

Recent investigations demonstrated that using an organized database containing both Structured Clinical and Demographic Information could significantly enhance the ability to predict Anaemia via Artificial Intelligence. Numerous studies have reported the development of more sophisticated Multivariate and Ensemble Models, which are able to use many different types of information (i.e., multiple hematological and demographic variables), in conjunction with their associated inter-relationships, in order to achieve improved predictive accuracy [12,13]. The introduction of Deep Learning and Attention-Based Architectures has strengthened Biomedical Predictions within higher-dimensional Data Sets through improved representations of Features and enhanced interpretability [14].

Concurrently, Medical Imaging has become an important tool for the identification of Anaemia non-invasively through systematic examination of the Conjunctiva. CNNs constructed using Conjunctival and Ocular Images identified minimal amounts of Pallor in the tear film associated with Hemoglobin Concentration, producing High Levels of Accuracy [15,16]. CNNs and Transformer-Based Models have been used to identify systemic diseases that are often indiscernible to the human eye and are only detectable via minute alterations of the Eye [17-19]. In addition, various applications utilising Deep Transfer Learning and Handcrafted Feature-Based Techniques with images of the Palpebral Conjunctiva have produced promising results in terms of Diagnostic Utility for Anaemia [20].

While these approaches have provided great opportunities for advancement, the use of images alone can frequently result in limitations due to a lack of clinical and environmental context, thus decreasing their effectiveness. Therefore, as a result of the investigations conducted recently, multimodal fusion has become increasingly important to improve the accuracy and generalizability of diagnoses[21,22]. With the introduction of transformer-based multimodal fusion methods with cross-attention mechanisms, researchers have demonstrated the ability to effectively integrate diverse sources of data, and explore connections that were previously difficult or impossible to find using unimodal data sets [23]. In addition, geographic data mining and geographic data modeling studies have indicated that including geographic and environmental characteristics is a critical consideration for making risk assessments of diseases [24]. Lastly, the results of recent studies using deep learning methods for segmenting the images have reinforced the need for unified fusion methods that combine visual, clinical, and contextual information as a means of achieving accurate identification of anemia [25]. Overview of key literature, methodological approaches and datatypes are shown in the Table 1.

Table 1. Summary of Key Literature in Anemia Prediction

Study / Reference	Data Type Used	Methodological Approach	Key Findings / Contributi	Identified Gaps
Zemariam et a (2024) [1]	Clinical & demograpl	Supervised ML (ensemb models)	Identified key predictors among adolescent girls; strong performance using structured data	No integration of images or spatial features
Turjo & Rahm (2024) [3]	Survey-based nutritic data	ML classification & forecasting	Modeled malnutrition risl among women; highlighte sociodemographic associations	Limited physiologic indicators; no multimodal fusior
Begum et al. (2024) [4]	Clinical & DHS dat	Gradient boosting mode	Effective prediction of nutritional status in pregna women	No visual or geospatial integratic
BS D et al. (202 [5]	Hematological marke	Explainable ML (XAI ensembles)	Identified influential bloo markers via SHAP	Used only lab data lacks imaging and spatial context
Pallavi et al. (2024) [9]	Conjunctival image	CNN-based image classification	Demonstrated feasibility c smartphone-based anemi detection	No clinical or geospatial correlate

3. Proposed AnemiaFusionNet Transformer Based Framework

The proposed architecture hypothesized here incorporates clinical text features, conjunctival image information, and geospatial features into a single learning framework for accurate detection of anemia. Every analysis medium contributes exclusive yet complementary information: with clinical biomarkers offering objective physiological measurements, ocular images that provides visual representation of pallor, and geospatial traits gathering population-level and environmental factors that impacts individual anemia risk. Through the integration of this disparate information, the architecture offers a means to transform the individual failing of unimodal models into a more advanced prediction methodology combines with how it will be used in practice, medically.

The Final Workflow of the proposed AnemiaFusionNet Model is shown in the Figure 1, from modality-specific preprocessing to feature extraction, transformer-based fusion, and final anemia classification. The Framework is developed to make sure that each modality is uniquely performed using best approaches before being merged into the same latent space through a cross-modal attention mechanism.

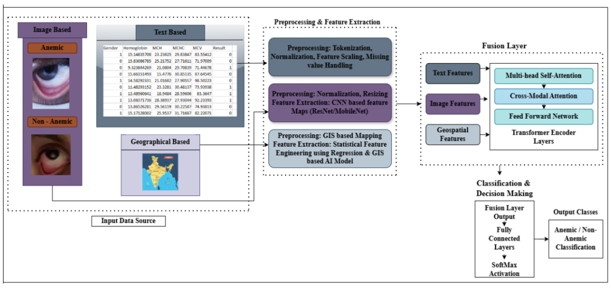

Figure 1. AnemiaFusionNet Architecture

3.1 Preprocessing and Feature Extraction

To ensure data compatibility and ideal feature representation among the different data modalities before being fused; each modality undergoes its own pre-processing pipeline. Clinical text-based data gets normalised, scaled, and cleaned to extract the structured haematology features. The image-type data is reduced in size (resized), normalised and denoised to capture the conjunctival pallor characteristics (as captured by the CNN-based feature extraction using image architectures such as ResNet or MobileNet). The processing of geospatial data is done via GIS-based methods, which include techniques for spatial encoding and feature engineering, and represent areas where regional anaemia occurs and environmental conditions. These steps will uniformly convert heterogeneous input types to embeddings that can be used for modality-specific transformers, ultimately leading to the creation of a single unique representation.

3.2 Fusion Layer

Cross-modal interaction between different models (for example; text/image/geospatial) occurs through fusing these types of modalities through the use of a transformer-based fusion layer, then enhancing salient features of the different models via multi-head self-attention, and further connecting complementary information across modals (i.e., linking hemoglobin levels from the text side with visual pallor cues from the image side) through cross-attention on all modals before generating a latent representation that captures complex relationships between the different models that were previously not detectable in the unimodal framework. By performing this fusing of modalities together with cross-attention, this increases the overall reliability of the visual representation created and provides additional accuracy to the overall diagnostic process of visual observation.

3.3 Classification and Deep Learning Module

The full Connective Layers followed by SoftMax Activation Function take the fused representation and use it to produce Anemia Classification output. The module distinguishes features associated with Anemia (indicating Users that have Anemia) from features associated with non-anemia (indicating Users that do not) and produces a probability distribution over these classifications. By combining numerous different sources of signal (clinical data, images and geography), the framework generates more precise and complete diagnoses of Anemia relative to any individual source of signal.

4. Materials and Methods

The Proposed AnemiaFusionNet architecture constructed to combine text based, image-based, and geospatial information for high-precision anemia detection. The methodology designed to combine the key abilities of structured Geospatial data from the National Family Health Survey (NFHS), physiological cues extracted from images, and environmental and contextual markers. Initially, each data undergoes processing and analysis individually to achieve standard performance, followed by a transformer-based fusion framework building relationship between various feature spaces with the help of cross attention layers.

4.1 Text Based Dataset

The Text based dataset consists of various blood test samples that helps in an evaluation for predicting the anemia. It includes Hemoglobin level, MCV, MCH and MCHC. Significantly it also includes data such as gender (0 for female and 1 for male) as well as label pointing whether the individual is anemic (1) or non-anemic (0). The dataset completely provides appropriate information to work on the supervised machine learning models to predict anemia. A full in-depth overview is given in Figure2.

Table 2. Overview of Text Based Dataset Used for Anemia Classification

Variable Nam	Description	Type	Units / Categories
Gender	Encoded biological sex of the subject	Categorical (0/	0 = Female, 1 = Male
Hemoglobin	Hemoglobin concentration used for anemia diagno	Numerical	g/dL
MCH	Mean Corpuscular Hemoglobin, average mass of H per RBC	Numerical	picograms (pg)
MCHC	Mean Corpuscular Hemoglobin Concentration	Numerical	g/dL
MCV	Mean Corpuscular Volume	Numerical	femtoliters (fL)
Result	Anemia status label derived from hemoglobin threshold	Binary Class	0 = non-anemic, 1 = Anemic

4.2 Image Dataset

The image dataset shows palpebral and conjunctival eyes. They are differentiated into two categorized i.e. anemic or not anemic groups. Each image was standardized to RGB format and underwent different parameters like resizing, illumination correction, and quality normalization to make sure consistency for deep learning-based feature extraction. Conjunctival vascularity and pallor intensity all medically known markers of anemia were retained in the image data and provides crucial visual for the CNN used in the AnemiaFusionNet framework workflow.

The photos present (A) the inner eyelid seems healthy and bright red, indicating that the individual's blood levels are normal and they are not anemic. As usually seen in anemia, the inner eyelid in (B) appears light pink, pale and less reddish. The pallor happens because low hemoglobin reduces the redness inside the eyelid.

Figure 2. A) Non-Anemic Image B) Anemic Image

The right side shows the extracted ROI generated during image preprocessing, which isolates the palpebral conjunctival band used for CNN-based feature extraction. The left side demonstrates the ocular anatomy with emphasis on the palpebral conjunctiva, located as the primary region of interest (ROI) for anemia detection because it is helpful in detecting conjunctival pallor.

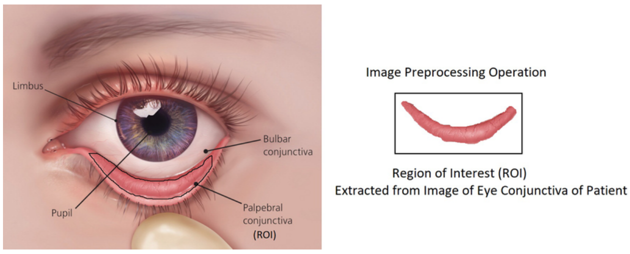

Figure 3. Anatomical Region of Interest (ROI) and ROI Extraction Process for Conjunctival Image Analysis

4.3 Geospatial Dataset

The geospatial dataset taken from NFHS-5 (2019-21), that presents state-level anemia prevalence among various demographic classes, including children, non-pregnant women, pregnant women, adolescents, and men. These markers show geographic disparities and population-level factors of anemia burden. The dataset validated spatial modeling, risk interpolation, and contextual integration within the AnemiaFusionNet framework.

State Wise Anemia Prevalence (NFHS-5)

Anemia distribution between different states and territories of India as per the NFHS5 has shown large geographical differences with respect to prevalence rates of anemia across Indian states. High prevalence rates were reported in northern areas, e.g., Ladakh (91.2%), Jammu and Kashmir (63.3%), West Bengal (64%), Gujarat (62.9%), and Eastern States (e.g., Tripura, 59.2%). These areas generally have high levels of malnutrition and socioeconomic disadvantage, which indicates an ongoing influence on the nutrition and overall health status. On the other hand, lower rates for example, in South India and Islands (Kerala, 33.9%), Goa (38.7%) and Lakshadweep (29.4%)), appear to correlate with their better health delivery systems and greater dietary diversity. Therefore, the regional differences found highlight the need to include the regional context in any predictive framework for anaemia.

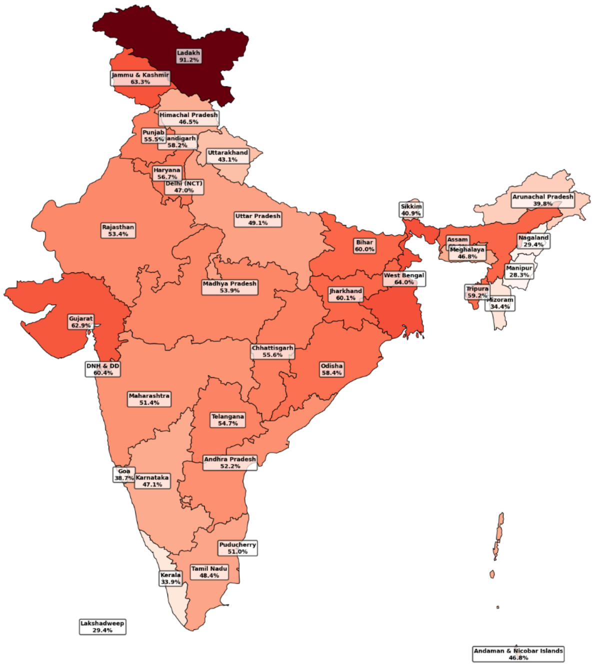

Figure 4. State Wise Anemia Prevalence in India Based on NFHS-5 Data

4.4 Modeling Framework

Unimodal models were independently developed using clinical, image-based, and geospatial data to assess the predictive contribution of each modality. The AnemiaFusionNet framework then integrated clinical textual features, image embeddings, and geospatial information as parallel inputs within a transformer architecture, where cross-attention layers enabled alignment and interaction across modalities.

5. Result Analysis:

This section represents a detailed analysis of the proposed AnemiaFusionNet architecture using text-based, Image based and Geographical based data.

5.1 Text Based Results

The text-based model was trained using structured clinical features, including hemoglobin, MCV, MCH, MCHC, and gender, to classify anemic and non-anemic cases. Trained on an openly accessible clinical anemia dataset, the model demonstrated strong performance using laboratory data alone, achieving an accuracy of 88.77%, precision of 84.06%, recall of 92.06%, an F1-score of 87.88%, and an ROC-AUC of 93.38%, indicating robust discriminative capability.

5.2 Image Based Results

The image classification model proved to be vigorously adept at forecasting when trained with conjunctival images pre-processed for ROI and CNN transfer learning models (MobileNetV2 and ResNet50). The visual cues of conjunctival redness, vascular engagement, and pallor were strongly embedded in the images to help learn adept discriminatory features for both anemic and non-anemic images. The model showed 100% accuracy, 100% precision, 100% recall, 100% F1-score, and an ROC-AUC of 1.000 for perfect class distinction.

5.3 Geospatial Based Results

Geospatial analysis was conducted using NFHS-5 state-wise prevalence of anemia to classify regions into low and high-risk groups based on a 4 percent cut-off. Logistic Regression was used as the comparison model for 36 states/UTs, indicating an accuracy of approximately 70%, precision of 75%, recall of 60%, F1-score of 67.7%, and ROCAUC of 76%. These values indicate relatively high variability and population-based characteristics of geospatial indicators as opposed to individual patient characteristics.

5.4 Proposed AnemiaFusionNet Results

The AnemiaFusionNet transformer integrates text-based clinical data, image features, and geospatial indicators into a unified learning framework, combining the strengths of individual modalities to capture complex anemia-related patterns that single-modality models fail to identify. The fused model achieved optimized performance, with an accuracy of 89.47%, precision of 92.86%, recall of 82.54%, an F1-score of 87.39%, and an ROC-AUC of 93.72%. As shown in Figure 5, the confusion matrix indicates accurate classification of both anemic and non-anemic cases with a notable reduction in false positives, outperforming image-only and geospatial-only models.

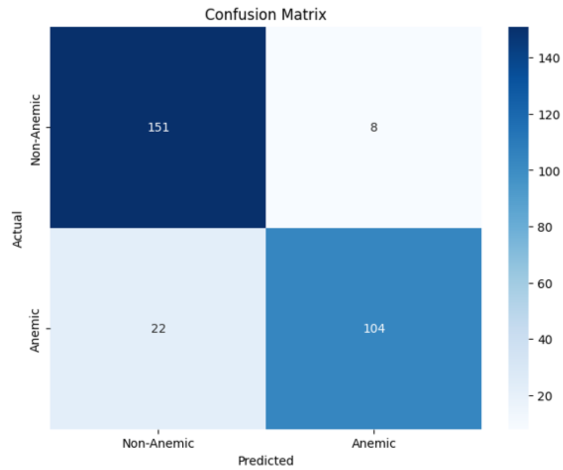

Figure 5. Confusion Matrix of AnemiaFusionNet (Text-Image-Geospatial) Fusion Model

6. Discussion

This study followed a progressive analytical strategy, beginning with unimodal models, extending to bimodal fusion, and culminating in the AnemiaFusionNet transformer-based framework. This stepwise approach enabled evaluation of individual modality strengths while demonstrating that integrating complementary information yields a more reliable, comprehensive, and clinically relevant system for anemia detection.

6.1 Unimodal Analysis

In the unimodal phase, separate predictive models were created for each type of data (text, image, and geographic) to examine how well each would perform independently from the others.

The text model contained hematological indicators including hemoglobin, MCV, and MCH, which produced an acceptable level of baseline performance; however, the text was unable to incorporate visual and contextual clues that would lead to incorrect interpretation in borderline/subtle cases. The image model produced a near-perfect level of performance because of the unique conjunctival pallor patterns present in this specific population; however, the small number of images led to issues regarding overfitting and inability to generalize to other populations. The geographic model was successful in modelling regional trends of anaemia and how socio-economic factors relate to anaemia; however, it could not be used for accurate individual diagnoses because it was based on aggregate data. Taken as a whole, the unimodal analyses have demonstrated that while each modality provides valuable information, the exclusivity of any one modality as the sole source limits the diagnostic capability and clinical relevance.

6.2 Bimodal Fusion

Bimodal fusion strategies were developed to overcome the limits of unimodal models by using combinations of complementary modes of information (Text – Images; Images – Geospatial; Geospatial – Text). Diagnostic sensitivity was improved with the Text – Image fusion as the combination of laboratory biomarker labs and conjunctival images enhanced the performance of ambiguous cases; however, performance is limited in areas where regional factors are important to diagnosis. The Image – Geospatial Fusion gave greater ability to interpret population-level risk due to placing the Visual Pallor in context with the regional patterns of Anemia, but, lacked utility for clinical prediction for an individual who does not have laboratory tests to work with. Geospatial – Text fusion combined clinical markers with socioeconomic status and the environment to increase the overall robustness of the bimodal model, but did not provide utility on cases in which visual pallor is necessary as a diagnostic factor. Bimodal models perform better than unimodal models but, without any one of the modalities represented fully, complete assessments of the risk of Anemia cannot be made, emphasizing the importance of employing Full Multimodal Integration.

6.3 AnemiaFusionNet Model: A Comprehensive Solution

The proposed AnemiaFusionNet transformer model combines all three modalities simultaneously Text, Image, and Geospatial data which enables cross-modal attention to learn interactions that unimodal and bimodal models are unable to capture. This detailed procedure:

i. reduces false negatives by combining visual, clinical, and contextual evidence,
ii. improves generalization across populations,
iii. balances precision and recall,
iv. captures subtle patterns missed by single or dual-source models, and
v. mirrors real clinical reasoning that synthesizes lab results, visual assessment, and environmental factors.

By addressing the limitations of both unimodal and bimodal approaches, the AnemiaFusionNet framework emerges as the most robust, accurate, and practical solution for large-scale anemia screening and regional risk mapping.

7. Conclusion and Future Scope

In this study, we develop a new framework for diagnosing anaemia (AnemiaFusionNet) using the transformer architecture. By integrating clinical biomarkers and Conjunctival Image feature extraction, an AnemiaFusionNet provides a robust solution for diagnosing anaemia based on incorporating clinical and geographic data together. The results of our analyses demonstrate that the AnemiaFusionNet model achieved superior performance levels than other unimodal models by fusing the complementary information provided by clinical biomarkers and geographic data; thus, very robust and reliable diagnostic capabilities were achieved. The AnemiaFusionNet will provide a comprehensive solution for diagnosing anaemia in most real-world situations through the combination of both an individual's clinical evidence and an aggregate of their environmental risk factors. As future research efforts expand the initial dataset to include more diverse and up-to-date data sources, additional image sources may be incorporated into future model development to help mitigate potential overfitting of individual images. We believe that both optimising the fusion process within a multimodal system (such as combining words, images, and geographic data) will further improve the predictive capabilities of the model.

8. References

[1] Zemariam AB, Yimer A, Kibret Abebe G, Wondie WT, Abate BB, Alamaw AW, et al. Employing supervised machine learning algorithms for classification and prediction of anemia among youth girls in Ethiopia. Sci Rep. 2024;14(1):9080. https://doi.org/10.1038/s41598-024-60027-4

[2] Daoud A, Jordán F, Sharma M, Johansson F, Dubhashi D, Paul S, et al. Using satellite images and deep learning

to measure health and living standards in India. Soc Indic Res. 2023;167(1):475–505. https://doi.org/10.1007/s11205-023-03112-x

[3] Turjo E, Rahman M. Assessing risk factors for malnutrition among women in Bangladesh and forecasting malnutrition using machine learning approaches. BMC Nutr. 2024;10(1):22. https://doi.org/10.1186/s40795-023-00808-8

[4] Begum N, Rahman M, Faruk MO. Machine learning prediction of nutritional status among pregnant women in Bangladesh: Evidence from Bangladesh Demographic and Health Survey 2017–18. PLoS ONE. 2024;19(5):e0304389. https://doi.org/10.1371/journal.pone.0304389

[5] BS D, Sharma P, Chadaga K, Sampathila N, Bairy G, Belurkar S, et al. An ensemble machine learning framework with explainable artificial intelligence for predicting haemoglobin-anaemia considering haematological markers. Syst Sci Control Eng. 2024;12(1):2420927. https://doi.org/10.1080/21642583.2024.2420927

[6] Bitew F. *Spatio-temporal inequalities and predictive models for determinants of undernutrition among women and children in Ethiopia* [dissertation]. San Antonio (TX): University of Texas at San Antonio; 2024.

[7] Gebeye L, Dessie E, Yimam J. Predictors of micronutrient deficiency among children aged 6–23 months in Ethiopia: A machine learning approach. Front Nutr. 2024;10:1277048. https://doi.org/10.3389/fnut.2023.1277048

[8] Sharma H, Singh S, Srivastava S. Socio-economic inequality and spatial heterogeneity in anaemia among children in India: Evidence from NFHS-4 (2015–16). Clin Epidemiol Glob Health. 2020;8(4):1158–1171. https://doi.org/10.1016/j.cegh.2020.04.009

[9] Pallavi, Basumatary B, Shukla R, Kumar R, Das B, Sahani A. A deep learning-based system for detecting anemia from eye conjunctiva images taken from a smartphone. IETE Tech Rev. 2024;41(3):274–286. https://doi.org/10.1080/02564602.2023.2242318

[10] Darshan B, Sampathila N, Bairy M, Belurkar S, Prabhu S, Chadaga K. Detection of anemic condition in patients from clinical markers and explainable artificial intelligence. Technol Health Care. 2024;32(4):2431–2444. https://doi.org/10.3233/THC-231207

[11] Kitaw B, Asefa C, Legese F. Leveraging machine learning models for anemia severity detection among pregnant women following ANC: Ethiopian context. BMC Public Health. 2024;24(1):3500. https://doi.org/10.1186/s12889-024-21039-x

[12] Qadah T, Munshi A. Synthesis and prediction of anemia from multi-data attribute co-existence. IEEE Access. 2024. https://doi.org/10.1109/ACCESS.2024.3510636

[13] Wulandari SA, Al Azies H, Naufal M, Prasetyanto WA, Zahra FA, et al. Breaking boundaries in diagnosis: Non-invasive anemia detection empowered by AI. IEEE Access. 2024. https://doi.org/10.1109/ACCESS.2024.3353788

[14] Sarkar A, Hossain SS, Sarkar R. Human activity recognition from sensor data using spatial attention-aided CNN with genetic algorithm. Neural Comput Appl. 2023;35(7):5165–5191. https://doi.org/10.1007/s00521-022-07911-0

[15] Wang Z, Keane PA, Chiang M, Cheung CY, Wong TY, Ting DSW. Artificial intelligence and deep learning in ophthalmology. In: Artificial Intelligence in Medicine. Cham: Springer; 2022. p.1519–1552. https://doi.org/10.1007/978-3-030-64573-1_200

[16] Patel PJ, Yevle D, Diwan D, Ranga S, Gandhi K, Dumasia S, et al. Performance analysis of deep learning algorithms for classifying chronic obstructive pulmonary disease. J Integr Sci Technol. 2024;12(2):745.

[17] Vadduri M, Kuppusamy P. Enhancing ocular healthcare: Deep learning-based multi-class diabetic eye disease segmentation and classification. IEEE Access. 2023. https://doi.org/10.1109/ACCESS.2023.3339574

[18] C B, AK P, TB K, P K. Automated anemia classification and hemoglobin level prediction using deep CNN and GLCM features of palpebral conjunctiva images. In: Proc IEEE Conf Information and Communication Technology (CICT); 2023. p.1–6. https://doi.org/10.1109/CICT59886.2023.10455477

[19] Mitani A, Huang A, Venugopalan S, Corrado GS, Peng L, Webster DR, et al. Detection of anaemia from retinal fundus images via deep learning. Nat Biomed Eng. 2020;4(1):18–27. https://doi.org/10.1038/s41551-019-0487-z

[20] Kharkar VP, Thakare AP. Design of multidomain feature analysis model for estimation of anemic conditions via deep transfer learning. IETE J Res. 2024;70(11):8323–8336. https://doi.org/10.1080/03772063.2024.2368645

[21] Yevle DV, Mann PS. Artificial intelligence-based waste management: A review of classification, techniques, issues, and challenges. WIREs Data Min Knowl Discov. 2025;15(2):e70025. https://doi.org/10.1002/widm.70025

[22] Bhatt D, Chopade M, Patel C, Yevle D. Foundations of neurosymbolic AI in Society 5.0. In: Society 5.0: A Transformation towards Human-Centered Artificial Intelligence. 2025. p.252. https://doi.org/10.1201/9781003643166-11

[23] Deng C-Y, Mitani A, Chen C-W, Peng L-H, Hammel N, Liu Y. Beyond predictions: Explainability and learning

from machine learning. 2023. p.199–218. https://doi.org/10.1007/978-3-031-24052-2_15

[24] Fathimabi SK, JayaLakshmi G, Suneetha M. Spatial data mining for prediction of unobserved zinc pollutants using various kriging methods. J Adv Environ Res Technol. 2023;1(3):57–64.

[25] Dhalla S, Maqbool J, Mann TS, Gupta A, Mittal A, Aggarwal P, et al. Semantic segmentation of palpebral conjunctiva using predefined deep neural architectures for anemia detection. Procedia Comput Sci. 2023;218:328–337. https://doi.org/10.1016/j.procs.2023.01.015