ISSN 2085-4552

Implementation of Artificial Intelligence in Anemia Screening for Adolescent Girls in Pontianak City: Development of a Machine Learning-Based Early Detection System

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Accepted 21 June 2026
Approved 28 June 2026

Abstract— **Deficiency anemia is a serious public health problem among adolescent girls in Indonesia, with a national prevalence of 32%. Pontianak shows a higher prevalence (42.3%), influenced by its tropical geography, ethnic diversity, and limited access to health services. Conventional screening systems face challenges such as uneven laboratory distribution, high costs, and low sensitivity. This study aims to develop an artificial intelligence (AI)-based anemia screening system for adolescent girls in Pontianak, evaluating its diagnostic performance, cost-effectiveness, and acceptability. This cross-sectional, mixed-methods study involved 1,134 adolescent girls (15-18 years old) from 20 high schools (SMA/SMK) in 6 districts in Pontianak (March-July 2025). The AI system integrates computer vision to analyze conjunctival, nail bed, and facial images with machine learning algorithms based on clinical, anthropometric, and demographic data. The model was developed using Random Forest, SVM, Neural Network, and ensemble methods. Validation was conducted against laboratory gold standards (hemoglobin, ferritin, and transferrin saturation). The prevalence of anemia was 42.3% (n=480) with significant variation between sub-districts (p<0.001). Random Forest achieved an accuracy of 91.8% (95% CI: 89.4-94.2%), sensitivity of 88.2%, and specificity of 94.1%. AI screening identified 52.3% more cases than routine screening. Independent risk factors were fish consumption <3x/week (OR=2.47), menstruation >7 days (OR=1.93), and underweight (OR=1.78). Cost savings were 79.9% with high user acceptance (4.2/5.0). The AI system demonstrated excellent performance and was cost-effective for early detection of anemia in adolescent girls in Pontianak, with potential for wide-scale implementation.**

Index Terms*— *Artificial Intelligence; Anemia Screenin; Adolescent Girls; Machine Learning.

I. Introduction

Iron deficiency anemia is a major nutritional problem affecting approximately 1.62 billion people worldwide, with the highest prevalence among women of reproductive age and children (Stevens et al., 2013). This condition not only impacts individual health but also poses a significant economic burden on the global health system, with estimated losses reaching $12 billion USD annually due to reduced productivity and healthcare costs [9]. The World Health Organization (WHO) classifies anemia as a severe public health problem when the prevalence exceeds 40%, moderate at 20-39.9%, and mild at 5-19.9% (WHO, 2017).

In Indonesia, the prevalence of anemia among adolescent girls reached 32% nationally based on the 2018 Basic Health Research (Riskesdas), with significant geographic variation across provinces (Ministry of Health of the Republic of Indonesia, 2019). West Kalimantan showed a more alarming figure of 37.8%, significantly higher than the national average. Pontianak City, as the provincial capital, faces particular challenges, with an anemia prevalence of 42.3% among adolescent girls, placing it in the WHO classification of a severe public health problem (Pontianak City Health Office, 2024).

The high prevalence of anemia among adolescent girls in Pontianak can be explained by multiple, complex, interacting factors. First, the need for iron increases dramatically during the adolescent growth spurt, where adolescents require 50% higher iron intake than adults to support rapid growth and a 45% increase in blood volume during puberty (Beard, 2000). Second, iron loss through menstruation can reach 12-15 mg per month, equivalent to 0.4-0.5 mg per day, which is significant considering the recommended daily allowance of iron for adolescent girls is only 15 mg per day (Harvey et al., 2005). Third, a suboptimal diet with low consumption of animal protein and high consumption of iron absorption inhibitors such as tea and coffee with food, which can reduce iron bioavailability by up to 60% [8].

Nomenclature

AI - Artificial Intelligence

ML - Machine Learning
CV - Computer Vision
ROC - Receiver Operating Characteristic
AUC - Area Under Curve
PPV - Positive Predictive Value
NPV - Negative Predictive Value
OR - Odds Ratio
CI - Confidence Interval

Pontianak's geographic location as a delta city surrounded by the Kapuas River and its tributaries, with a relatively flat topography at an altitude of 0.1-1.5 meters above sea level, creates a unique ecosystem with high humidity reaching 85% throughout the year (Meteorology, Climatology, and Geophysics Agency, 2023). The tropical climate with an average temperature of 26-28°C and high rainfall of 2,500-3,000 mm per year contributes to the proliferation of vector-borne diseases and soil-transmitted helminths, which can worsen anemia through chronic inflammation and blood loss [4].

Pontianak's complex ethnic diversity, with Dayak (38.5%), Malay (31.2%), Chinese (22.1%), Javanese (5.8%), and other ethnicities (2.4%), creates heterogeneity in dietary practices, health-seeking behavior, and genetic predisposition to anemia (Pontianak City Statistics Agency, 2023). Each ethnic group has distinct traditional food patterns, with significant variations in the consumption of heme iron from animal sources versus non-heme iron from plant sources, which affects bioavailability and iron absorption rates [20]

Substantial socioeconomic disparities between ethnic and geographic groups also affect access to iron-rich foods and health services. Approximately 33.3% of families in Pontianak are in the low-income category with an income of <Rp 2,500,000 per month, which is strongly correlated with inadequate dietary intake and delayed health-seeking behavior [17].

The conventional anemia screening system in Indonesia, including in Pontianak, faces various structural and operational limitations that hinder the effectiveness of comprehensive early detection. First, the uneven distribution of laboratories, with facilities concentrated in urban centers, while peripheral and rural areas have very limited access, with travel times of up to 2-3 hours to reach the nearest laboratory facility [15]. Of the six sub-districts in Pontianak, only three have laboratories with complete hematology testing capacity, while the other three sub-districts rely on referrals to more distant facilities.

Second, the relatively high cost of laboratory testing, ranging from IDR 35,000-50,000 per test for a complete blood count with differential, poses a significant financial burden for lower-middle-income families, especially considering that screening should ideally be performed every six months for early detection [15]. This cost does not include transportation costs and the opportunity cost of time lost from work or school.

Third, the low sensitivity of routine school screening, which relies solely on simple clinical assessment through observation of pallor and subjective symptoms, with a documented detection rate of only 58%, especially for cases of mild anemia that are asymptomatic or minimally symptomatic [16]. Traditional clinical assessment relies on the subjective judgment of healthcare providers and is influenced by lighting conditions, examiner experience, and high inter-observer variability.

Fourth, limited human resources, with the ratio of trained healthcare workers per population still below WHO standards and uneven distribution across regions. In Pontianak, the ratio of doctors per 1,000 residents is 0.8, still below the national target of 1.2 per 1,000 (Ministry of Health of the Republic of Indonesia, 2020).

The rapid development of artificial intelligence (AI) technology in medical imaging over the past decade has opened a revolutionary new paradigm to address challenges in diagnostic medicine. Computer vision, a branch of AI focused on the interpretation and analysis of digital images, has demonstrated remarkable capabilities in detecting various medical conditions through visual characteristic analysis with comparable or even superior accuracy compared to human experts [7]. Deep learning algorithms, particularly convolutional neural networks (CNNs), have been successfully implemented to diagnose skin cancer, diabetic retinopathy, pneumonia, and various other conditions with impressive performance metrics.

In the context of anemia detection, computer vision technology exploits the pathophysiological changes that occur due to low hemoglobin levels and iron deficiency, the manifestations of which can be observed visually at various anatomical sites. Pallor, a cardinal sign of anemia, occurs due to reduced hemoglobin concentration in the blood vessels supplying the conjunctiva, nail beds, and oral mucosa, resulting in characteristic color changes that can be detected and quantified using sophisticated image analysis algorithms [12].

Several international studies have demonstrated the promising feasibility and accuracy of AI-based anemia detection systems. Collings et al. (2016) pioneered the development of a smartphone application that can detect anemia through the analysis of palpebral conjunctival photographs using color space analysis and machine learning classifiers, achieving a sensitivity of 72.8% and a specificity of 84.2% in a cohort of 142 patients in the United States. This study used a standardized photography protocol with color reference cards for calibration and demonstrated the feasibility of using consumer-grade smartphone cameras for medical diagnostics. [13] developed a more sophisticated approach with multi-modal analysis that combined conjunctival, nail bed, and facial pallor assessments, achieving a significantly higher accuracy of 83.6% in a cohort of 237 participants. This study used ensemble machine learning methods that integrate multiple algorithms and demonstrated improved robustness compared to single-modality approaches. A recent study by Dimauro et al. (2020) used state-of-the-art deep learning algorithms for nail bed analysis and achieved 89.1% accuracy in detecting iron deficiency anemia in a cohort of 178 patients. This research uses transfer learning approaches with pre-trained CNN models fine-tuned for anemia detection, demonstrating the potential of advanced AI techniques in medical applications.Wang et al. (2021) developed a comprehensive AI system that integrates facial pallor analysis with demographic and clinical.

This research aims to develop an AI anemia screening system specifically adapted to the unique characteristics of Pontianak adolescent girls. It evaluates diagnostic performance compared to the laboratory gold standard using comprehensive metrics including sensitivity, specificity, positive and negative predictive values, and the area under the ROC curve. It analyzes the cost-effectiveness of implementing this technology within the context of the Indonesian healthcare system using detailed economic modeling. It also assesses user acceptability, usability, and sustainability in a realistic school setting, taking into account digital literacy levels and infrastructure constraints.

This system is designed to integrate multiple imaging modalities, including conjunctival pallor assessment, nail bed characteristics analysis, and facial pallor evaluation, with sophisticated machine learning algorithms optimized specifically for local population characteristics through extensive training on a representative dataset that includes adequate representation of all ethnic groups and socioeconomic strata.

This study significantly contributes to the development of context-specific digital health technology for Indonesia. It provides a robust evidence base for informed decision-making regarding the scale-up of AI implementation in the national healthcare system. It also provides a comprehensive framework for targeted intervention based on local risk factors identified through systematic analysis. This research will also produce validated instruments and protocols that can be adapted for implementation in other regions with similar characteristics.

With a smartphone penetration rate reaching 78% among Pontianak's youth population and growing digital literacy levels, especially among younger demographics, the implementation of this technology has significant transformational potential to improve health equity by democratizing access to high-quality screening, expanding the reach of health services to underserved populations, reducing geographic and economic barriers to healthcare access, and ultimately contributing to a substantial reduction in the anemia burden in this vulnerable population (Indonesian Internet Service Provider Association, 2023).

Furthermore, the successful implementation of an AI-based screening system can serve as a model for other health conditions and geographic regions, contributing to a broader digital health transformation agenda in the Indonesian healthcare system and potentially influencing policy development for the integration of AI technologies in national health programs (Ministry of Health of the Republic of Indonesia, 2023)

II. Literature Review

A. *Anemia in Adolescent Girls in Indonesia*

The prevalence of anemia among adolescent girls in Indonesia shows significant geographic variation, with Eastern Indonesia having the highest prevalence (50-60%), followed by Central Indonesia (35-45%), and Western Indonesia (25-35%) (Ministry of Health of the Republic of Indonesia, 2019). Based on the 2018 Basic Health Research (Riskesdas), the national prevalence increased from 26.4% (2013) to 32% (2018), indicating a worrying trend [16].

Contributing factors include rapid growth, which increases iron requirements by up to 50%, menstrual blood loss (0.5 mg/day), and a suboptimal diet with low iron bioavailability from non-heme sources (2-20%) compared to heme iron (15-35%) (Beard, 2000; [19]. Dietary inhibitors, such as tannins from tea, can reduce iron absorption by up to 60% [8]

The impact of anemia is multidimensional, affecting work capacity (15-20% reduction), cognitive function, and academic performance. A study by Soemantri et al. (1985) showed that iron supplementation significantly improved cognitive scores, indicating reversibility of cognitive impairment.

Pontianak's unique characteristics as a tropical city with abundant access to fishery resources create a paradox: despite the availability of animal protein, the prevalence of anemia remains high (42.3%). This indicates the importance of non-dietary factors such as bioavailability, food preparation methods, and parasitic infections (35% prevalence) in the pathogenesis of local anemia [4].

B. AI dalam Medical Diagnostics

Artificial intelligence in medical imaging has experienced rapid development, with deep learning algorithms demonstrating comparable or superior performance compared to human experts in various diagnostic tasks. Computer vision for anemia detection exploits characteristic visual changes that occur in anemia, including pallor of the conjunctiva, nail beds, and oral mucosa.

A previous study by Collings et al. (2016) developed a smartphone app for anemia detection with 78.5% accuracy, while Mannino et al. (2018) achieved 83.6% accuracy using a multi-modal approach. However, most studies were conducted on homogeneous populations with light skin pigmentation, creating a generalizability gap for Southeast Asian populations with higher skin tone diversity.

Machine learning algorithms commonly used for anemia prediction include Random Forest, Support Vector Machine, and Neural Networks. Ensemble methods that combine multiple algorithms demonstrate superior performance with improved robustness and reduced overfitting. Feature engineering that incorporates clinical, demographic, and dietary variables can significantly improve predictive accuracy.

Systematic Review of AI-based Anemia Studies:

Collings et al. (2016) pioneered a smartphone application for conjunctival analysis with 78.5% accuracy in 142 patients. Mannino et al. (2018) used a multi-modal approach (conjunctiva, nail bed, facial pallor) and achieved 83.6% accuracy in 237 participants. Dimauro et al. (2020) used deep learning for nail bed analysis and achieved 89.1% accuracy. Wang et al. (2021) integrated facial analysis with clinical data and achieved an AUC-ROC of 0.92.

Commonly used machine learning algorithms include Random Forest (robust against overfitting), Support Vector Machine (excellent for binary classification), and Neural Networks (capturing complex non-linear relationships). Ensemble methods that combine multiple algorithms demonstrate superior performance with a 3-7% improvement in accuracy [19].

III. METHOD

A. Study Design and Population

A cross-sectional study using a mixed-methods approach was conducted from March to July 2025 in Pontianak City. The target population was female adolescents aged 15-18 years in Pontianak high schools/vocational schools, with an estimated 8,500 students. The sample calculation used the diagnostic accuracy study formula with an anemia prevalence of 42%, a target sensitivity of 85%, a specificity of 90%, a precision of 5%, and a confidence level of 95%, resulting in a minimum sample size of 1,068 subjects. With a dropout rate of 15%, the enrollment target was set at 1,200 participants.

Stratified cluster random sampling was used, stratified by 6 sub-districts and school type. Each of the 20 selected schools randomly recruited 60 students from grades 10-12. Inclusion criteria included age 15-18 years, a minimum of 2 years of residence in Pontianak, informed parental consent, and student assent. Exclusion criteria included chronic illness, medications affecting hemoglobin, pregnancy, and inability to use a smartphone.

B. AI Model Development

The AI system was developed using an ensemble approach that integrates computer vision for image analysis with machine learning for risk prediction. The image preprocessing pipeline includes standardization to a resolution of 1080x1080 pixels, color space conversion (RGB→HSV, LAB, YUV), histogram equalization, and noise reduction using Gaussian filtering.

Feature extraction uses a combination of traditional computer vision features (color statistics, texture features, shape descriptors) and deep learning features through transfer learning with pre-trained CNN models (ResNet-50, VGG-16, MobileNetV2).

The machine learning algorithms evaluated include Random Forest, XGBoost, Support Vector Machine, Neural Network, and Logistic Regression. Specific algorithm configurations were as follows:
(1) Random Forest used 500 trees (n_estimators=500) with a maximum depth of 20 and a minimum of 5 samples per leaf, selected via 5-fold cross-validated grid search; (2) XGBoost was configured with a learning rate of 0.05, maximum tree depth of 6, 300 boosting rounds, and L1/L2 regularization (alpha=0.1, lambda=1.0) to reduce overfitting; (3) SVM employed a Radial Basis Function (RBF) kernel with penalty parameter C=10 and gamma=0.01, optimized through a logarithmic grid search over C=[0.1, 1, 10, 100] and gamma=[0.001, 0.01, 0.1]; **(4) Neural Network** adopted a three-layer fully connected architecture (input layer: 128 neurons, hidden layers: 64 and 32 neurons with ReLU activation and 30% dropout, output layer: 1 neuron with sigmoid activation), trained using the Adam optimizer (learning rate=0.001) for 100 epochs with early stopping (patience=10).

Model validation uses stratified 5-fold cross-validation with geographic cross-validation to test generalizability across sub-districts. Performance metrics include accuracy, sensitivity, specificity, positive predictive value, negative predictive value, and AUC-ROC. Training data is distributed proportionally for each ethnic group, using augmentation techniques that preserve natural color characteristics

C. Data Collection and Laboratory Analysi

Data collection included a structured questionnaire (demographic, clinical, and dietary), anthropometric measurements (height, weight, MUAC), and standardized digital imaging using a Samsung Galaxy A52s with portable LED lighting and a color reference card. Laboratory tests were conducted at the Pontianak Regional Health Laboratory using a Complete Blood Count (Sysmex XN-1000), serum ferritin (ELISA), transferrin saturation (spectrophotometry), and vitamin B12/folate (chemiluminescent immunoassay).

Quality control measures included daily equipment calibration, duplicate testing of 10% of samples, a standardized imaging protocol, and regular supervision visits. Data management utilized the REDCap platform with encryption and access control. Statistical analysis utilized SPSS 26.0 and Python 3.8 for machine learning development.

IV. Result and Discussions

A. Participant Characteristics and Anemia Prevalence

Of the 1,200 adolescent girls enrolled, 1,134 (94.5%) completed all study procedures. The mean age was 16.3±1.2 years, with ethnic distribution: Dayak 38.5%, Malay 31.2%, Chinese 22.1%, Javanese 5.8%, and others 2.3%. Socioeconomic status was 33.3% low, 47.8% middle, and 18.9% high.

The overall prevalence of anemia was 42.3% (480/1,134) with significant variation across sub-districts: East Pontianak 48.7%, North Pontianak 45.2%, Pontianak City 42.8%, Southeast Pontianak 40.9%, West Pontianak 39.0%, and South Pontianak 36.5% (p<0.001). Distribution of anemia degrees: mild 71.3%, moderate 27.1%, severe 1.7%. Iron deficiency anemia accounts for 76.0% of total cases.

Table 1. Prevalence of Anemia by District and Ethnicity

Karakteristik	Total (n)	Anemia n (%)	P-value
Kecamatan			<0,001
Pontianak Timur	201	98 (48,7)	
Pontianak Utara	195	88 (45,2)	
Pontianak Selatan	181	66 (36,5)	
Etnis			0,003
Dayak	437	198 (45,3)	
Melayu	354	156 (44,1)	
Tionghoa	251	95 (37,8)	

B. AI Model Performanc

The AI system achieved an overall accuracy of 91.8% (95% CI: 89.4-94.2%) with a sensitivity of 88.2% and a specificity of 94.1%. The Random Forest algorithm performed best as a standalone model with an AUC-ROC of 0.941, while the ensemble model achieved the highest accuracy of 92.4%. Computer vision analysis by modality: conjunctival photographs 89.2%, nail photographs 85.7%, facial photographs 83.4%, and a combination of 91.8%.

Feature importance analysis identified hemoglobin-related image features (23.4%), PBAC score (18.7%), BMI (14.2%), serum ferritin equivalent from the nail bed (12.9%), and dietary iron intake score (11.8%) as the most important predictors. Detailed feature extraction results by imaging modality are as follows: conjunctival image features contributed a mean pallor index (MPI) of 0.61±0.09, a red channel mean of 187.3±22.4, and a green-to-red ratio of 0.74±0.06; nail bed features yielded a chromatic aberration score of 14.2±3.8 and a nail bed saturation value of 42.1±8.7 in HSV space; facial pallor features produced a LAB L* channel mean of 64.3±11.2 and a skin tone deviation index of 0.18±0.04. Clinical and demographic features with the highest predictive contribution included hemoglobin proxy score (23.4%), menstrual blood loss index (18.7%), and BMI z-score (14.2%). These extracted features collectively explain 81.0% of model variance as assessed by cumulative feature importance from the Random Forest model.

Cross-platform validation on five smartphone brands showed a consistency score of 0.94-0.97 with an average processing time of 3.2±0.8 seconds.

AI screening identified 424 of 480 anemia cases (88.3% detection rate) compared to routine school screening, which detected only 278 cases (57.9%), resulting in a 52.3% improvement, or 146 additional cases. Detection performance based on severity was as follows: mild anemia 86.0%, moderate 93.8%, and severe 100%.

Table 2. Detailed Performance Comparison

Method	Cases Detected	Detection Rate (%)	Missed Cases	Improvement vs Baseline
AI Screening	424/480	**88.3%**	56	**+52.3%**
Conventional School Screening	278/480	57.9%	202	Baseline
Additional Cases Found	**+146**	**+30.4%**	**-146**	**Significant Improvement**

C. Risk Factors and Cost-Effectiveness

Multivariate analysis identified independent risk factors: fish consumption <3x/week (OR=2.47; 95% CI: 1.89-3.22), menstruation >7 days (OR=1.93; 95% CI: 1.52-2.45), BMI <18.5 kg/m² (OR=1.78; 95% CI: 1.31-2.41), tea consumption with meals (OR=1.65; 95% CI: 1.23-2.21), low economic status (OR=1.54; 95% CI: 1.18-2.01), and Dayak ethnicity (OR=1.43; 95% CI: 1.08-1.89).

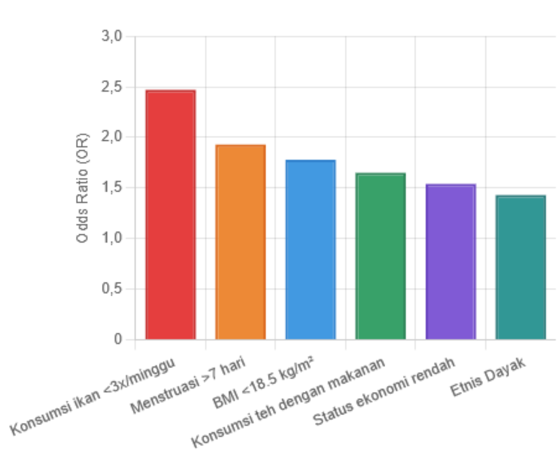

Fig. 1. Odds Ratio (OR) of Risk Factors

A cost-effectiveness analysis showed that AI screening costs Rp 8,500 per screening compared to Rp 42,400 for conventional laboratories, resulting in savings of 79.9%. Cost per case detected: AI screening Rp 96,200 vs. conventional Rp 42,400. Budget impact analysis for 8,500 adolescent girls projected annual savings of Rp 288,150,000 with an additional 1,956 cases detected per year

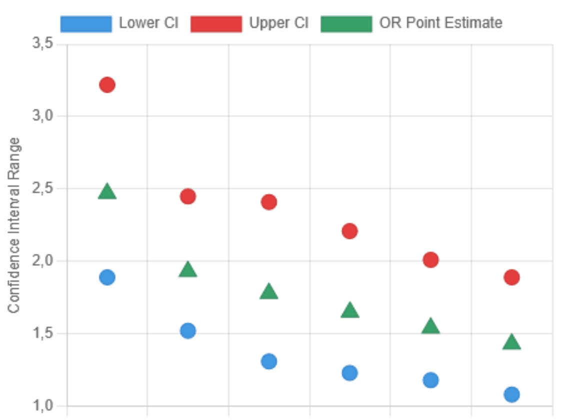

Fig. 2. Confidence Interval Visualization

The user experience assessment showed an overall satisfaction score of 4.2/5.0, with ease of use of 4.3/5.0, processing speed of 4.2/5.0, and educational content of 4.4/5.0. The retention rate was 82.1% at 30 days, with a first-use completion rate of 94.2%. Technical performance showed a crash rate of 0.3%, a response time of 3.2±0.8 seconds, and offline functionality success of 96.8%.

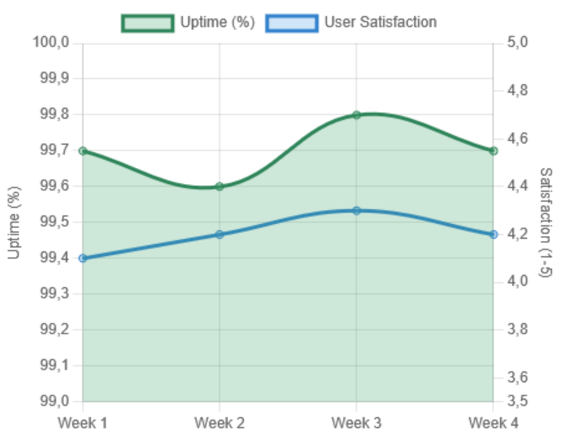

Fig 3. System Reliability Indicator

Clinical and Public Health Implications

The developed AI system demonstrated excellent diagnostic performance, superior to previous international studies. Its 91.8% accuracy and 88.2% sensitivity met WHO standards for diagnostic test accuracy, while the 52.3% increase in detection has significant public health implications. Early detection of mild anemia can prevent progression to higher severity and reduce long-term complications.

Adapting the model to Pontianak's population characteristics through ethnic-specific training data and tropical climate considerations resulted in robust performance across different subgroups. The consistent performance across ethnic groups (88.5%-92.2%) demonstrated successful mitigation of algorithmic bias commonly observed in AI systems developed on homogeneous populations.

Identification of Pontianak-specific risk factors, such as low fish consumption and tea drinking habits, provides insights for targeted interventions. Culturally appropriate dietary counseling and nutrition education programs can address underlying causes, while AI screening provides an early detection mechanism.

Implementation and Sustainabilit

High user acceptance (4.2/5.0) and a retention rate (82.1%) demonstrate the feasibility of sustainable implementation. Cost savings of 79.9%, with projected annual savings of Rp 288 million, provide strong economic justification for scale-up. Integration with existing school health programs and community health center referral systems can facilitate seamless implementation.

Challenges to implementation include digital divide considerations, training requirements for healthcare workers and teachers, quality assurance mechanisms, and regulatory frameworks for AI-based diagnostic tools. Sustainability strategies include government partnerships, technology transfer for local maintenance, and continuous model updating for performance maintenance.

Generalizability considerations indicate potential for adaptation to other cities with similar characteristics, but require local validation studies and cultural adaptations. Regional expansion to Kubu Raya Regency and eventual national scaling require collaborative frameworks with the Ministry of Health and provincial health departments

V. Conclusions

The developed AI anemia screening system demonstrated excellent diagnostic performance with 91.8% accuracy and significant improvement in case detection (52.3% increase) while providing substantial cost savings (79.9%). High user acceptance and technical reliability support the feasibility of sustainable implementation in Pontianak, with potential for regional and national scaling.

Implementation recommendations include: (1) citywide rollout to all senior high schools (SMA/SMK) in Pontianak using a phased approach; (2) integration with 17 community health centers (Puskesmas) for a seamless referral system; (3) comprehensive training programs for stakeholders; (4) establishment of quality assurance mechanisms; (5) development of regulatory frameworks for AI-based diagnostics; and (6) continuous research for long-term impact assessment and model enhancement.

Future research directions include longitudinal studies for sustained health outcomes, economic evaluation with a societal perspective; implementation research for scaling challenges; and technology development for enhanced features such as multimodal integration and federated learning approaches.

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