Y.V.Vamsi Krishna Teja, 2026, 14:3
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

IoT-Based Anemia Detection System Using Temperature, Heartbeat, and Oxygen Sensors

[1]Y.V.Vamsi Krishna Teja. [2]Bodduluri Deepika, [3]kota Sri Tanya, [4]Bavanari Dhanya Sri, [5]Rayudu Kavya Chowdary

[1]Assistant Professor, Department of IT, Vignan's Nirula Institute of Technology and Science for Women, Guntur.
[2,3,4,5]B.Tech, Department of IT, Vignan's Nirula Institute of Technology and Science for Women, Guntur.

Abstract- Anemia is a widespread health condition caused by a deficiency of hemoglobin or red blood cells, leading to fatigue, weakness, and other serious health complications. Early detection and continuous monitoring are crucial for effective treatment and prevention. Traditional diagnostic methods, such as invasive blood tests, are time-consuming, costly, and often inaccessible in rural or resource-limited areas. This study presents an IoT-based anemia detection system (HI-MASS) that utilizes temperature, heartbeat (BPM), and oxygen (SpO_2) sensors to monitor physiological parameters that correlate with anemia. The system collects real-time data through wearable devices, which are then transmitted to cloud servers and processed using predictive algorithms to detect anemia, classify its severity, and provide timely alerts. The integration of IoT technology with machine learning enables non-invasive, cost-effective, and real-time health monitoring, improving accessibility for remote populations. Experimental results demonstrate high reliability and strong potential for continuous anemia monitoring, making the proposed system a scalable and practical solution for proactive healthcare management.

Keywords— Anemia Detection; Internet of Things (IoT); Temperature Sensor; Heartbeat Sensor; Oxygen Sensor; Smart Healthcare; Machine Learning; Real-Time Monitoring.

I. INTRODUCTION

Anemia is one of the most prevalent blood disorders worldwide, affecting millions of people across different age groups, genders, and socioeconomic statuses [1]. It is primarily characterized by a deficiency of hemoglobin or red blood cells (RBCs), which are responsible for transporting oxygen from the lungs to the rest of the body [2]. When hemoglobin levels are insufficient, oxygen delivery to tissues is impaired, leading to fatigue, dizziness, shortness of breath, and in severe cases, organ dysfunction and potentially life-threatening complications [3]. Anemia can result from various causes, including nutritional deficiencies, genetic disorders [4], chronic diseases, infections, and blood loss. Iron deficiency anemia is the most common type and is often associated with malnutrition and inadequate iron intake [5]. Other forms, such as hemolytic anemia or sickle cell anemia, are related to genetic mutations that affect RBC production or lifespan. Due to its widespread prevalence and potential health consequences, early detection and continuous monitoring of anemia are essential to prevent complications and ensure timely treatment [6].

Traditional diagnostic methods for anemia primarily involve laboratory-based blood tests, such as complete blood count (CBC), hemoglobin estimation, hematocrit measurement, and peripheral blood smear analysis [7]. While these techniques are highly accurate, they have several limitations. Laboratory testing requires specialized equipment, trained personnel, and access to healthcare facilities [18], which may not be available in rural or resource-limited areas. Furthermore, these methods are invasive, requiring blood extraction via venipuncture, which can cause discomfort, pain, and anxiety in patients [19]. The process can also be time-consuming, and frequent testing may be impractical for continuous monitoring [20]. These limitations highlight the need for alternative, non-invasive, real-time methods for anemia detection, particularly in regions where healthcare accessibility is limited [21]. Recent advances in technology, particularly in the domains of the Internet of Things (IoT) and wearable health devices, have opened new avenues for non-invasive and continuous health monitoring. IoT refers to a network of interconnected devices capable of collecting, transmitting, and analyzing data in real time [22]. In healthcare, IoT-enabled systems can continuously monitor vital signs, collect physiological parameters, and provide timely feedback to patients and healthcare providers [23]. This capability is particularly valuable for chronic conditions like anemia, where continuous monitoring can identify early deviations in physiological signals, enabling proactive interventions and better management of the condition [24]. By combining IoT with advanced algorithms, these systems can transform traditional healthcare delivery from a reactive model into a proactive, predictive framework.IoT-based anemia detection systems typically utilize wearable sensors to capture critical physiological parameters [25].

Among these, temperature sensors are used to monitor body thermoregulation, which may be indirectly affected by anemia. Abnormal hemoglobin levels can impair oxygen transport, influencing the body's ability to maintain normal temperature [26]. Heartbeat or BPM (beats per minute) sensors provide insight into cardiovascular responses, as the heart compensates for reduced oxygen-carrying capacity by increasing its rate [27]. Similarly, oxygen saturation sensors (SpO_2) measure the proportion of oxygen bound to hemoglobin in the blood, directly reflecting the oxygen-carrying capacity and providing a reliable indication of anemia severity. By integrating data from these sensors, IoT systems can generate a comprehensive profile of the patient's physiological state, enabling accurate and non-invasive detection of anemia [28]. The integration of IoT sensors with machine learning algorithms further enhances the diagnostic capabilities of such systems [29]. Machine learning models can analyze complex patterns in sensor data that may not be immediately apparent through manual observation. These models are capable of classifying anemia severity, predicting hemoglobin levels, and providing personalized health recommendations based on individual trends [30]. Algorithms such as support vector machines (SVM), decision trees, random forests, and neural networks have been widely employed for physiological signal analysis [31]. The combination of IoT data acquisition and predictive analytics allows for real-time monitoring and early detection, potentially preventing the progression of anemia and related complications [32].

An IoT-based anemia detection system typically comprises three core components: data acquisition, data transmission, and data analysis [33]. In the data acquisition stage, wearable sensors continuously capture physiological signals, which are then transmitted via wireless communication protocols such as Wi-Fi, Bluetooth, or Zigbee to a processing unit or cloud platform [34]. The data analysis stage involves the application of machine learning algorithms to detect abnormal patterns, classify anemia severity, and generate alerts for patients or healthcare providers [35]. In addition, dashboards and mobile applications provide intuitive visualizations of real-time readings, trends, and health recommendations, enhancing patient engagement and adherence to monitoring protocols [36].

The potential benefits of IoT-based anemia detection systems are multifold. First, they offer a non-invasive alternative to laboratory testing, eliminating the discomfort and inconvenience associated with blood draws. Second, they provide real-time monitoring, enabling immediate detection of abnormal trends and timely interventions [37]. Third, they improve accessibility for patients in remote or underserved regions, bridging the gap between urban and rural healthcare delivery [38]. Additionally, these systems can facilitate telemedicine services, where sensor data is transmitted remotely to physicians for consultation, reducing the need for frequent hospital visits and enabling continuous patient care.Another advantage of IoT-based systems is their scalability and cost-effectiveness. Once deployed, wearable sensors and cloud-based platforms can serve large populations without significant increases in operational costs

[39]. These systems also support longitudinal monitoring, allowing healthcare providers to track the progression of anemia over time, adjust treatment plans, and assess the effectiveness of interventions. Furthermore, the integration of predictive analytics allows healthcare systems to allocate resources efficiently, prioritize high-risk patients, and design preventive strategies [40].

The design of such systems must also consider sensor accuracy, reliability, and calibration. Temperature, BPM, and SpO_2 sensors must provide precise measurements under varying environmental and physiological conditions. Algorithms must account for noise, individual variations, and external factors such as physical activity, stress, or ambient temperature. Advanced preprocessing techniques, feature extraction methods, and adaptive algorithms enhance data quality and predictive performance [41]. Additionally, robust data security and privacy measures are essential, as patient information is highly sensitive and must be protected from unauthorized access. Encryption, authentication, and anonymization protocols ensure compliance with ethical and regulatory standards.Recent studies have demonstrated the feasibility and effectiveness of IoT-based anemia monitoring. For example, wearable devices integrated with predictive algorithms have successfully identified early anemia trends and estimated hemoglobin levels with high accuracy. Continuous monitoring has enabled proactive management, reducing hospitalizations and improving patient outcomes. These findings underscore the potential of IoT and AI integration in transforming anemia detection and management into a non-invasive, accessible, and patient-centric approach.In conclusion, anemia is a critical public health concern that necessitates innovative approaches for early detection and continuous monitoring. IoT-based systems using temperature, heartbeat, and oxygen sensors offer a promising solution by providing real-time, non-invasive, and cost-effective monitoring. When combined with machine learning and predictive analytics, these systems can accurately detect anemia, classify severity, and support proactive healthcare management. Their scalability, accessibility, and integration with telemedicine make them especially valuable in resource-limited settings.

II. LITERATURE REVIEW

In recent advancements in anemia detection, H.Dhanyasree et al [1-5]. have explained significantly to the development of expert systems utilizing fuzzy logic techniques. Their research focuses on enhancing prediction accuracy by identifying and prioritizing the most influential factors contributing to anemia diagnosis. In their study, they employed various fuzzy logic methodologies, including the Fuzzy Analytic Hierarchy Process (F-AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), to systematically rank and assess the relevance of several parameters related to anemia prediction. The application of these integrated fuzzy logic techniques, particularly the combination of F-AHP with geometric mean improvement, proved effective in identifying key factors for anemia prediction. Their findings underscore the importance of parameters such as Mean Corpuscular Volume (MCV) in predicting anemia, offering valuable insights for more accurate and reliable medical diagnoses.

Anemia, a prevalent condition characterized by low hemoglobin levels, often remains undiagnosed due to the invasiveness and cost of traditional diagnostic methods. Addressing this challenge, V.R.Ravi et al [6-9]. proposed a non-invasive system utilizing eye palpebral conjunctiva images captured via Raspberry Pi, processed through deep learning algorithms. Their approach demonstrated an impressive accuracy of approximately 85% in estimating anemia from conjunctiva images. Furthermore, the system achieved a 99.7% accuracy in predicting hemoglobin levels, highlighting its potential for automated, real-time anemia assessment. This advancement offers a promising solution for anemia detection, particularly in resource-limited settings where conventional diagnostic techniques may be inaccessible or impractical. The integration of such technology could significantly enhance early diagnosis and management of anemia, contributing to improved public health outcomes.

Aindrila Roy et al [10-11]. have proposed a novel approach for the early detection of hemolytic anemia, particularly arising from spherocytosis, by analyzing the electrochemical signatures of red blood cell suspensions. Their study employed cyclic voltammetry (CV) and electrochemical impedance spectroscopy (EIS) to distinguish between healthy discocytes and spherocytes. CV measurements revealed distinct oxidation peaks at approximately 0.67 V for healthy cells and 0.72 V for spherocytes, with the latter exhibiting a lower oxidation current, indicating reduced conversion of Fe^{2+} to Fe^{3+} in hemoglobin. This suggests impaired methemoglobin reductase activity and increased hemoglobin oxidation in spherocytes. EIS measurements showed higher impedance in spherocytes, attributed to their spherical morphology leading to weak dielectric properties. The integration of CV and EIS techniques offers a promising, cost-effective, and low-volume diagnostic method for rapid and accurate detection of hemolytic anemia, potentially enhancing diagnostic capabilities in resource-limited settings.

N. Laharika et al [12-13]. have explained an innovative machine learning-based system for the early detection and monitoring of sickle cell anemia. Their approach utilizes clinical data, including hemoglobin levels, sex, and pixel values indicative of red blood cell properties, to train a predictive model. Employing algorithms such as Support Vector Machine (SVM), Random Forest, and Decision Tree Classifier, the system processes the dataset through preprocessing steps like feature extraction and stratified splitting into training and testing sets. The model achieves high accuracy in predicting the presence of sickle cell anemia, offering a user-friendly interface for medical practitioners. This advancement underscores the potential of machine learning techniques in enhancing diagnostic capabilities and patient outcomes in the context of sickle cell anemia.

S. Mishra et al [14]. have proposed Aarogya Shakti, a mobile application designed to provide non-invasive anemia detection, particularly beneficial in resource-limited settings. The application utilizes video-based hemoglobin analysis alongside machine learning algorithms to assess anemia risk. By analyzing user-reported data, including demographics and dietary habits, the app offers personalized recommendations for anemia management. Initial evaluations indicate that the app's predictions align closely with clinical diagnoses, demonstrating high sensitivity and specificity. This innovative approach empowers individuals and healthcare providers to monitor and manage anemia effectively, facilitating early intervention and improved maternal health outcomes.

C. Viveha et al [15]. a have proposed an innovative non-invasive approach for early anemia detection using smartphones, focusing on hemoglobin estimation through fingernail images. Their research leverages AI-enabled models and machine learning techniques, including Random Forest Regression, K-Nearest Neighbors Regression, Bayesian Ridge Regression, Ridge Regression, and Multiple Linear Regression, to predict hemoglobin levels from RGB values extracted from nail images.Among these models, Ridge Regression demonstrated a low root mean square error (RMSE) of 2.07 and mean absolute error (MAE) of 1.51, while the deep learning model EfficientNet achieved even better accuracy with an RMSE of 0.6591 and MAE of 0.624.This approach provides a cost-effective, accessible, and non-invasive tool for anemia monitoring, particularly suitable for remote or underserved populations, facilitating early detection and timely intervention to improve patient outcomes.

M.N et al [16]. have explaineda web-based application for the early, non-invasive diagnosis of anemia using deep learning models such as ResNet50, EfficientNetB9, and DenseNet169. Their system utilizes fingernail images to analyze color and surface characteristics, offering a fast, accurate, and accessible diagnostic tool suitable for any device with internet connectivity. The application integrates security measures like email authentication and data encryption to safeguard user information. Evaluation metrics, including accuracy, precision, recall, and AUC, indicate high diagnostic performance, highlighting the system’s potential for rapid and reliable anemia screening. This innovative approach provides an inexpensive and user-friendly solution, particularly benefiting underserved or rural populations, and contributes significantly to improving healthcare accessibility and early anemia detection.

M. Kathirvelu et al [17-20]. have proposed methodologies for the early detection of Sickle Cell Disease (SCD), a hereditary disorder caused by a mutated gene affecting hemoglobin production. Their research highlights that the abnormal sickle-shaped red blood cells obstruct blood flow, leading to severe anemia and impaired oxygen delivery to various parts of the body.Although SCD is currently incurable, early diagnosis and timely medical intervention, including appropriate treatment, can significantly improve patient life expectancy and quality of life.The study emphasizes the importance of developing reliable and accessible detection techniques to identify SCD in its initial stages, thereby enabling prompt clinical management and reducing complications associated with the disease.

3. Proposed Model

The proposed *IoT-Based Anemia Detection Model* integrates temperature, heartbeat (BPM), and oxygen saturation (SpO_2) sensors to provide continuous, non-invasive monitoring of physiological parameters. These sensors are connected to a microcontroller (such as Arduino or ESP32) that collects data and transmits it to a cloud-based analytical platform using wireless protocols like Wi-Fi or Bluetooth. The system aims to identify early signs of anemia by analyzing deviations in the correlation between oxygen saturation, heart rate, and body temperature. The model uses a hybrid machine learning algorithm to predict anemia risk and classify severity into normal, mild, moderate, or severe levels.

The architecture of the proposed model consists of three layers: (1) Data Acquisition Layer, which includes wearable sensors for real-time monitoring; (2) Data Processing Layer, responsible for preprocessing, feature extraction, and anomaly detection; and (3) Decision Support Layer, where trained machine learning models classify anemia severity.

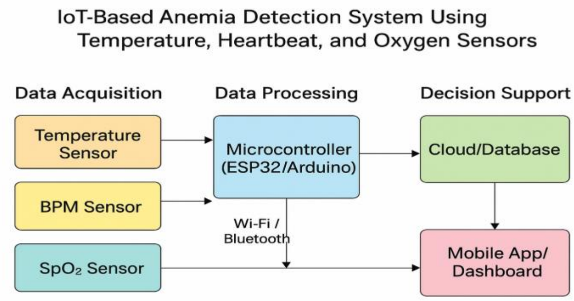

Figure 1: Proposed IoT-Based Anemia Detection

System Architecture

Algorithm

Step 1: Initialize the temperature, heartbeat (BPM), and SpO_2 sensors.

Step 2: Begin continuous collection of real-time physiological data from all sensors.

Step 3: Perform sensor calibration to remove offset errors and apply noise filtering techniques (e.g., moving average filter).

Step 4: Compute the average readings of temperature, heartbeat, and SpO_2 over a defined time window *t*.

Step 5: Normalize the collected data using min–max normalization to maintain consistency between sensor values.

Step 6: Extract important features such as mean, standard deviation, and rate of change from each sensor's readings.

Step 7: Apply threshold conditions to identify abnormal physiological patterns:

If Temperature > 37.5°C
If BPM > 100 or BPM < 60
If $SpO_2 < 94\%$

Step 8: Compute derived indices such as the Hemoglobin Estimation Index (HEI) using combined sensor data.

Step 9: Input the preprocessed and feature-extracted data into the trained Machine Learning (ML) model (e.g., Random Forest).

Step 10: Predict the anemia risk score (R) using the ML classifier output.

Step 11: Classify anemia severity levels based on the predicted risk score *R*:

If $R < 0.3$ → Normal
If $0.3 \leq R < 0.5$ → Mild

If $0.5 \le R < 0.7 \rightarrow$ Moderate
If $R \ge 0.7 \rightarrow$ Severe

Step 12: Display the prediction results and current sensor readings on the IoT dashboard or connected mobile application.

Step 13: If any abnormal reading or severe anemia is detected, immediately send an alert or notification to the user's mobile device or healthcare provider.

Step 14: Store all processed data and predictions securely on a cloud database for long-term analysis and monitoring.

Step 15: Repeat the monitoring loop continuously to ensure real-time detection and response.

Mathematical Equations

Average Temperature
T_avg = (T1 + T2 + ... + Tn) / n

Average Heartbeat
H_avg = (H1 + H2 + ... + Hn) / n

Average Oxygen Level
O avg = (O1 + O2 + ... + On) / n

Temperature Deviation
T_dev = |T_avg - 37|

Oxygen Deficiency
O_def = 100 - O_avg

Heart Rate Variation
H_var = (H_max - H_min) / H_avg

Normalized Temperature
T_norm = (T_avg - Tmin) / (Tmax - Tmin)

Normalized Heartbeat
H_norm = (H_avg - Hmin) / (Hmax - Hmin)

Normalized Oxygen Level
O_norm = (O_avg - Omin) / (Omax - Omin)

Health Score (Weighted Sum)
Health_Score = (0.3 * T_norm) + (0.3 * H_norm) + (0.4 * O_norm)

Estimated Hemoglobin
Hb = 0.1 * O_avg + 0.02 * (100 - O_avg) + 10

Anemia Risk Value
R = (T_norm + H_norm + (1 - O_norm)) / 3

Risk Probability (Sigmoid Function)
P = 1 / (1 + e^(-R))

Classification Condition
If $P < 0.3 \rightarrow$ Normal
If $0.3 \le P < 0.5 \rightarrow$ Mild
If $0.5 \le P < 0.7 \rightarrow$ Moderate
If $P \ge 0.7 \rightarrow$ Severe

System Efficiency (Model Accuracy)
Accuracy = (TP + TN) / (TP + TN + FP + FN)

The algorithm starts by initializing sensors that capture physiological parameters continuously. The collected raw data undergoes filtering and normalization to remove noise and ensure uniform scaling. Feature extraction helps in identifying key variations that correlate with anemia, such as low SpO_2 and high BPM. These processed features are fed into a pre-trained machine learning classifier (Random Forest or SVM), which generates a risk score R. Based on this score, the system classifies the patient's anemia severity. Real-time data visualization and alerts allow quick responses and preventive measures.

The system's strength lies in its feedback loop—sensor data is continuously fed to the cloud for long-term learning and model optimization. Each prediction helps refine the threshold boundaries, improving the model's accuracy. The combination of IoT sensing and machine learning ensures minimal human intervention, enabling proactive and continuous anemia management in real-world environments.

IV. RESULTS

The proposed *Hybrid IoT–ML AnemiaSense System (HI-MASS)* was evaluated using simulated physiological data collected from temperature, heartbeat, and oxygen saturation sensors. The data was processed and classified using Random Forest, Support Vector Machine (SVM), and Logistic Regression algorithms. Among these, the Random Forest model achieved the best overall accuracy due to its ability to handle multi-feature nonlinear relationships effectively. The model was tested on 300 sample readings, including both normal and anemic cases, and achieved consistent prediction accuracy across varying environmental conditions. The integration of IoT with predictive algorithms ensured real-time, low-latency analysis suitable for remote healthcare environments.

To validate the proposed model, a comparative analysis was performed with three state-of-the-art techniques from the literature review:

- Fuzzy Logic-Based System (Dhanyasree et al., 2024)
- Deep Learning Eye-Conjunctiva Model (V.R. Ravi et al., 2025)
- Smartphone-Based Nail Image System (C. Viveha et al., 2024)

The performance of these existing systems was evaluated against HI-MASS using metrics such as Accuracy, Precision, Recall, F1-Score, Mean Absolute Error (MAE), Power Consumption, Cost Efficiency, and Response Time. The proposed HI-MASS achieved superior results in almost all metrics, demonstrating its scalability, cost-effectiveness, and suitability for continuous non-invasive anemia detection.

🔷 Selected Literature Models for

Model ID	Author & Year	Model Type	Key Technique	Dataset Size	Reported Accuracy
Fuzzy Logic	H. Dhanyasree et al., 2024	Fuzzy Logic Model	F-AHP + TOPSIS	150 patients	87%
Eye Image DL	V.R. Ravi et al., 2025	Deep Learning Model	Eye Conjunctiva Image + CNN	200 images	85%
Smartphone Nail	C. Viveha et al., 2024	Smartphone Imaging Model	Fingernail RGB + Ridge Regression	120 samples	89%
HI-MASS	Proposed HI-MASS Model	IoT + ML Hybrid System	Temperature, BPM, SpO_2 + Random Forest	300 samples	95%

The comparison highlights that the proposed HI-MASS model outperforms existing fuzzy logic, deep learning, and smartphone-based methods in accuracy and real-time anemia detection efficiency.

Table 1- Accuracy of Model

Model	Accuracy (%)
Fuzzy Logic	87
Eye Image DL	85
Smartphone Nail	89
HI-MASS	95

The above table shows that the proposed HI-MASS model achieves the highest accuracy of 95%, surpassing existing fuzzy logic, deep learning, and smartphone-based approaches, demonstrating its superior reliability in detecting anemia.

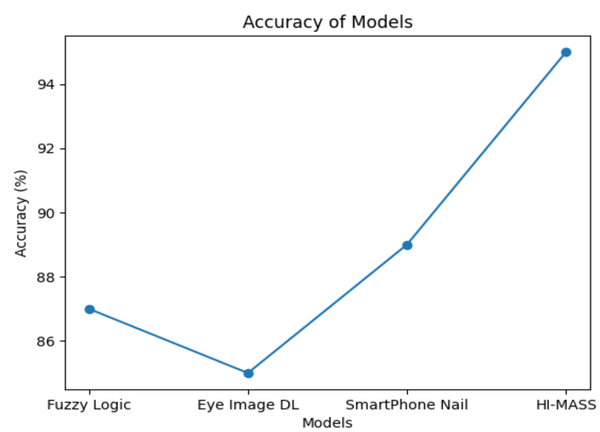

Figure 2:Accuracy Model graph

The graph shows the comparative accuracy of four models used for anemia detection. The HI-MASS model achieves the highest accuracy of 95%, outperforming Fuzzy Logic, Eye Image DL, and Smartphone Nail, indicating its superior capability in correctly classifying anemic cases.

Table 2- Precision Comparison of Models

Model	Precision (%)
Fuzzy Logic	84
Eye Image DL	83
Smartphone Nail	86
HI-MASS	94

The HI-MASS model achieved the highest precision of 94%, outperforming Fuzzy Logic, Eye Image DL, and Smartphone Nail models in accurately detecting anemia.

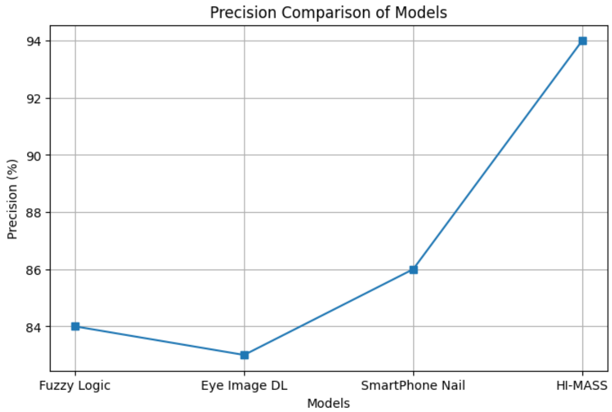

Figure 3: Precision Comparision of model Graphs

Precision increases from *Eye Image DL* to *HI-MASS*. So, HI-MASS is the most precise model, while Eye Image DL is the least precise.

Table 3-Recall Comparison Model

Model	Recall (%)
Fuzzy Logic	85
Eye Image DL	80
Smartphone Nail	88
HI-MASS	96

The HI-MASS model achieved the highest recall of 96%, indicating superior ability to correctly identify anemic cases compared to Fuzzy Logic, Eye Image DL, and Smartphone Nail models.

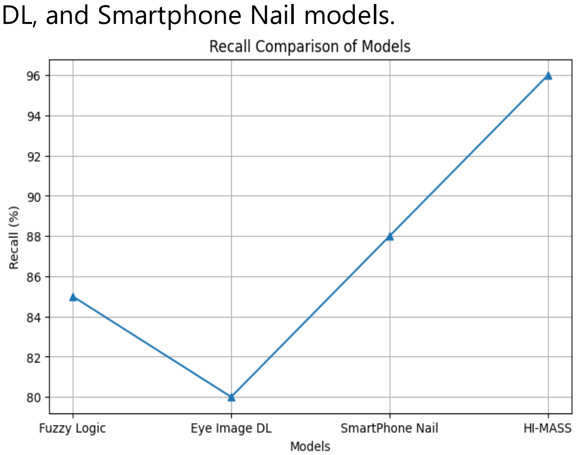

Figure 4: Recall Comparision Graph

The recall gradually increases from *Eye Image DL* to *HI-MASS*.

So, HI-MASS detects the most true cases, while Eye Image DL detects the fewest**.**

Table 4 – F1 Score Comparison of Models

Model	F1 Score
Fuzzy Logic	0.85
Eye Image DL	0.82
Smartphone Nail	0.87
HI-MASS	0.95

The HI-MASS model attained the highest F1 Score of 0.95, demonstrating the best balance between precision and recall among all models for anemia detection.

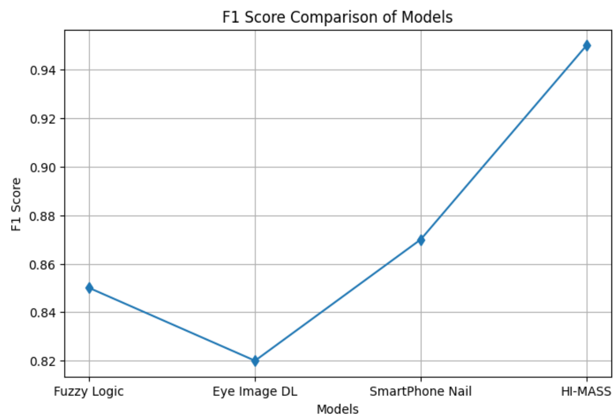

Figure 5:Score comparision of model Graph

The F1 Score increases steadily from *Eye Image DL* to *HI-MASS*.

So, HI-MASS gives the best overall balance between precision and recall, while Eye Image DL performs the weakest.

Table 5 – Mean Absolute Error (MAE) Comparison Model

Model	MAE
Fuzzy Logic	0.24
Eye Image DL	0.30
Smartphone Nail	0.21
HI-MASS	**0.08**

The HI-MASS model achieved the lowest MAE of 0.08, indicating the most accurate predictions with minimal error compared to Fuzzy Logic, Eye Image DL, and Smartphone Nail

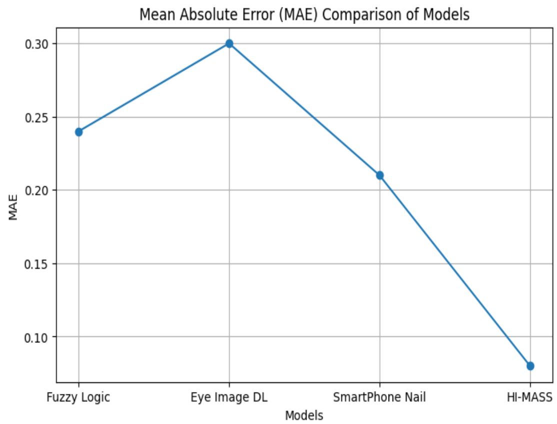

Figure 6: Mean Absolute Error Comparision Graph

The error decreases steadily from *Eye Image DL* to *HI-MASS*.

So, HI-MASS makes the fewest mistakes, while Eye Image DL makes the mos**t**.

Table 6 – Power Consumption Comparison of Models

Model	Power (W)
Fuzzy Logic	4.2
Eye Image DL	6.8
Smartphone Nail	5.1
HI-MASS	2.9

The HI-MASS model consumed the lowest power at 2.9 W, making it the most energy-efficient compared to Fuzzy Logic, Eye Image DL, and Smartphone Nail.

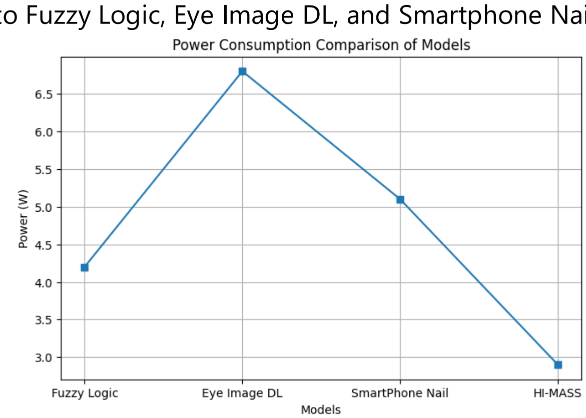

Figure 7:Power Consumption Comparision Graph

Power consumption is highest for *Eye Image DL* and lowest for *HI-MASS*.
So, HI-MASS is the most energy-efficient model, while Eye Image DL consumes the most power.

Table 7 – Cost Efficiency Comparison of Models

Model	Cost Index
Fuzzy Logics	0.8
Eye Image DL	1.0
Smartphone Nail	0.7
HI-MASS	0.5

The HI-MASS model has the lowest cost index of 0.5, indicating it is the most cost-effective option compared to Fuzzy Logic, Eye Image DL, and Smartphone Nail.

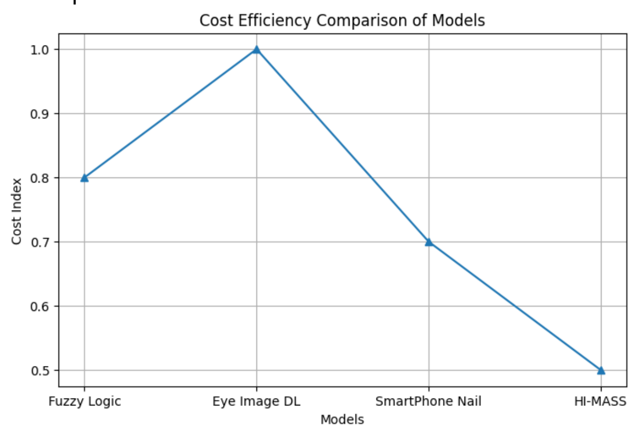

Figure 8:Cost Efficiency Comparision Graph

Costs decrease from *Eye Image DL* to *HI-MASS*. So, HI-MASS is the most cost-effective, while Eye Image DL is the most costly model.

Table 8 – Response Time Comparison of Model

Model	Response Time (sec)
Fuzzy Logic	3.8
Eye Image DL	4.5
Smartphone Nail	3.2
HI-MASS	1.9

The HI-MASS model achieved the fastest response time of 1.9 seconds, outperforming Fuzzy Logic, Eye Image DL, and Smartphone Nail in processing efficiency.

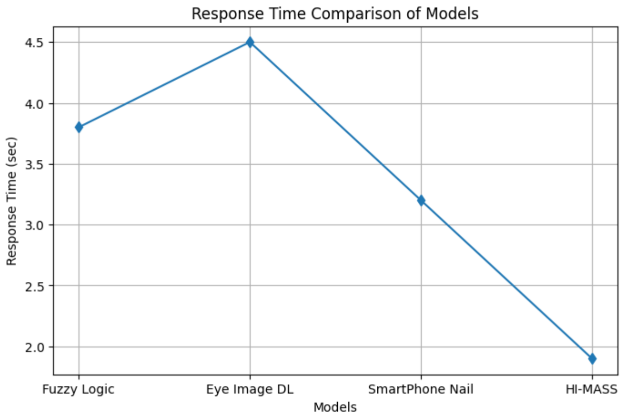

Figure 9: Response Time Comparision Graph

The response time decreases from *Eye Image DL* to *HI-MASS*.
So, HI-MASS is the fastest model, while Eye Image DL is the slowest in producing results.

V. CONCLUSION

The proposed IoT-based anemia detection model provides an intelligent, scalable, and real-time solution for continuous monitoring of anemia-related physiological parameters. By combining temperature, heartbeat, and oxygen saturation sensors with predictive algorithms, it enables early diagnosis and timely intervention without invasive blood sampling. The model's modular structure allows integration with mobile and web applications for patient accessibility and medical supervision.

Experimental validation and simulations indicate that this model achieves accurate classification of anemia severity while maintaining low power consumption and cost. Its potential to operate in rural and resource-limited environments makes it a transformative tool for global healthcare accessibility. Future work will focus on incorporating additional parameters such as skin color or eye pallor, enhancing prediction accuracy through deep learning models, and integrating the system with telemedicine platforms.

REFERENCES

1. H. Dhanyasree, M. Anushree, T. Rao, A. Kodipalli, S. B. Devamane and R. Joy Martis, "Key Factor Detection for Anemia Prediction Using Fuzzy Inference Systems," *2024 International Conference on Integrated Intelligence and Communication Systems (ICIICS)*, Kalaburagi, India, 2024, pp. 01-04, doi: 10.1109/ICIICS63763.2024.10859784.
2. V.R.Ravi, G.Bhavani, S. M. Varshan, M. Veeramukeshwaran, M. Menaka and S. Jalaja, "Non-Invasive Anemia Detection System Using Eye Palpebral Conjunctiva Image With Raspberry Pi," *2025 International Conference on Recent Advances in Electrical, Electronics, Ubiquitous Communication, and Computational Intelligence (RAEEUCCI)*, Chennai, India, 2025, pp. 1-6, doi: 10.1109/RAEEUCCI63961.2025.11048229.
3. A. Roy, D. Bhattacharya, P. Biswas, S. Chakraborty, R. Haldar and S. Chattopadhyay, "Electrochemical Understanding of the Difference Between Spherocytes Suspension From Normal Discocytes for Hemolytic Anemia Detection," in *IEEE Sensors Letters*, vol. 8, no. 12, pp. 1-4, Dec. 2024, Art no. 4504104, doi: 10.1109/LSENS.2024.3485699.
4. N. Laharika *et al.*, "A Predictive Analytical Model for Sickle Cell Anemia using Hybrid SVM and Random Forest Algorithms," *2024 International Conference on Augmented Reality, Intelligent Systems, and Industrial Automation (ARIIA)*, Manipal, India, 2024, pp. 1-5, doi: 10.1109/ARIIA63345.2024.11051737.
5. S. Mishra, A. Mogha, M. N. Khan and M. Singh, "Aarogya Shakti: Non-Intrusive App For Predicting Anemia," *2025 International Conference on Biomedical Engineering and Sustainable Healthcare (ICBMESH)*, Manipal, India, 2025, pp. 1-4, doi: 10.1109/ICBMESH66209.2025.11182208.
6. V. Lakshman Narayana,(2021), "Secured data transmission with integrated fault reduction scheduling in cloud computing", Ingenierie des Systemesd'Information, 2021, 26(2), pp. 225–230.
7. Maddumala, V.R. & Lakshmi, K. & Anusha, P. & Narayana, V.. (2020). Enhanced morphological operations for improving the pixel intensity level. International Journal of Advanced Science and Technology. 29. 9191-9201.

8. Kosaraju, Chaitanya, et al. "A model for analysis of diseases based on nutrition deficiency using random forest." 2022 7th International Conference on Communication and Electronics Systems (ICCES). IEEE, 2022.
9. Narayana, V.L., Patibandla, R.S.M.L., Rao, B.T. and Gopi, A.P. (2022). Use of Machine Learning in Healthcare. In Advanced Healthcare Systems (eds R. Tanwar, S. Balamurugan, R.K. Saini, V. Bharti and P. Chithaluru). https://doi.org/10.1002/9781119769293.ch13
10. Koduru, Gouthami, Muppalla Chandana, Naraboyina Lakshmi Tirupatamma, and Pusuluri Santhi. "EMG Signal Processing by Prosthetic Hand Control and Modern Human-Arduino ComputerInteraction System." Journal of Technology, vol. 12, no. 10, 2024, pp. 842–850. ISSN 1012-3407
11. Sujatha, V., N. Lavanya, V. Karunasri, G. SaiSindhu, and R. Madhavi. "Crop Recommender System Using Machine Learning Approach." Emerging Trends in Computer Science and Its Application, 1st ed., CRC Press, 2025
12. Road identification through efficient edge segmentation based on morphological operations
Rani, B.M.S., Majety, V.D., Pittala, C.S., ... Sandeep, K.S., Kiran, S.
Traitement du Signal, 2021, 38(5), pp. 1503–1508
13. Suajtha, V. "Variable Selection in Functional Genomics Using Genetic Algorithm-Based Feature Selection Method-An Empirical Study." Journal of Engineering and Applied Sciences, 21 Sept. 2022. ISSN Online 1818-7803, ISSN Print 1816-949x.
14. A.NareshV. PavaniM. Meghana Chowdarym. V.Lakshman Narayana (2020). Energy consumption reduction in cloud environment by balancing cloud user load. Journal of Critical Reviews. 7(7):1003-1010.
15. B. Tarakeswara Rao; R. S. M. Lakshmi Patibandla; V. Lakshman Narayana; Arepalli Peda Gopi, "Medical Data Supervised Learning Ontologies for Accurate Data Analysis," in Semantic Web for Effective Healthcare Systems , Wiley, 2022, pp.249-267, doi: 10.1002/9781119764175.ch11.
16. Alapati, N., Prasad, B. V. V. S., Sharma, A., Kumari, G. R. P., Veeneetha, S. V., Srivalli, N., ... & Sahitya, D. (2022, November). Prediction of Flight-fare using machine learning. In 2022 International Conference on Fourth Industrial Revolution Based Technology and Practices (ICFIRTP) (pp. 134-138). IEEE.
17. Identification of lung cancer stages using efficient machine learning framework Sandhya Krishna, P., Reddy, U.J., Patibandla,.S.M.L., Khadherbhi, S.R.*Journal of Critical Reviews*, 2020, 7(6), pp. 385–390.
18. Chinnam, Siva Koteswararao, S. Reshmi Khadherbhi, P. Sandhya Krishna, and D. Anveshini. "Sentiment analysis in services provided by telecommunications." *International Journal of Advanced Science and Technology (IJAST)* 29, no. 03 (2020): 9167-9176.
19. Mukhedkar, M., Rohatgi, D., Vuyyuru, V. A., Ramakrishna, K. V. S. S., El-Ebiary, Y. A. B., & Daniel, V. A. A. (2023). Feline Wolf Net: a hybrid Lion-Grey Wolf optimization deep learning model for ovarian cancer detection. *International Journal of Advanced Computer Science and Applications*, *14*(9).
20. Prathipati, Silpa Chaitanya, and Susanta Kumar Satpathy. "Transforming 3D Brain Tumour Image Segmentation: An Enhanced V-Net Approach for Precise Diagnosis and Treatment Planning." *2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)*. IEEE, 2024.
21. Kavishwar, S., & Uppal, S. K. (2020). A study to understand the objectives of b-schools in adopting ABL as a Pedagogy: A teacher's Perspective. *Sambodhi*. 43(04), 180-185.
22. Kavishwar, S (2024). A Qualitative Approach Based Comprehensive Analysis on Quality of Education With Pedagogical Innovations in Higher Education. *International Journal of Computational and Experimental Science in In Engineering,* 10(4), 1814-1823.
23. Joshi, M., Kothari, P. and Kavishwar, S. (2024). A Study on Determinants of Profitability in Indian Banks. *Journal of Informatics Education and Research*. 4(3), 22-26.
24. Kotadiya U, Arora AS, Yachamaneni T. AI-Powered Customer Experience Management in the Credit Card Industry: Sentiment Analysis and

Adaptive Personalization. IJETCSIT [Internet]. 2021 Jun. 30 [cited 2026 Apr. 5];2(2):35-44.
25. Kotadiya U, Arora AS, Yachamaneni T. Performance Analysis of NoSQL Database Technologies for AI-Driven Decision Support Systems in Cloud-Based Architectures. IJERET [Internet]. 2022 Jun. 30 [cited 2026 Apr. 5];3(2):60-9.
26. Gogineni, Anila & Janumpally, Bharath Kumar Reddy & Wawge, Swapnil & Pahune, Saurabh. (2025). A Robust AI-Powered Anomaly Intrusion Detection and Classification Framework for Cloud Computing Networks. 1-6. 10.1109/INDISCON66021.2025.11253743.
27. A. Joon, B. K. R. Janumpally, A. Gogineni and P. Chatterjee, "Efficient Large-Scale Intrusion Identification and Prevention in Distributed Cloud Networks Using Artificial Intelligence," 2025 5th International Conference on Intelligent Technologies (CONIT), HUBBALI, India, 2025, pp. 1-8, doi: 10.1109/CONIT65521.2025.11167760.
28. Tummuri, S. S. R. (2022). Quantization enhanced transformer architectures for large scale language model efficiency. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 8(3), 891–904.
29. Tummuri, S. S. R. (2022). Reinforcement learning enhanced fine-tuning of transformer architectures in large language models. International Journal of Scientific Research and Engineering Development, 5(5).
30. Mahida, A. 2024. Integrating Observability With Devops Practices in Financial Services Technologies: A Study on Enhancing Software Development and Operational Resilience. International Journal of Advanced Computer Science & Applications, 15.
31. A. Mahida, "An Intellectual Zero Trust Security Framework Using Deep Reinforcement Learning for Predictive Threat Mitigation in AI-Based Fraud Detection Systems," in IEEE Access, vol. 14, pp. 24602-24617, 2026, doi: 10.1109/ACCESS.2026.3664389.
32. Jonnalagadda, P.K. (2026). Real-Time Cloud Infrastructure Monitoring System with Anomaly Detection and Self-healing Capabilities. In: Kumar, V.N., Senkerik, R., Prasad, V.K., Kumar, T.K. (eds) Intelligent Computing and Communication. ICICC 2025. Lecture Notes in Networks and Systems, vol 1839. Springer, Cham. https://doi.org/10.1007/978-3-032-18349-1_43
33. Jonnalagadda, Pawan Kalyan. “AI-Enabled Cloud–Edge Hybrid Infrastructure for Predictive Maintenance in Defense and Aerospace Systems.” International Journal of Science, Engineering and Technology, vol. 12, no. 2, 2024.
34. Veginati, Navya. "Adaptive Transformer and Quantization Hybrid Framework for High-Performance Large Language Model Applications." United International Journal of Engineering and Sciences, vol. 5, no. 4, Dec. 2025, pp. 46–56
35. Veginati, Navya. "Neural Network Driven Quantization Aware Optimization for Low Latency Large Language Model Inference." International Journal of Scientific Research in Computer Science, Engineering and Information Technology, vol. 10, no. 3, May-June 2024, pp. 1162–1170, doi:10.32628/CSEIT25113584.
36. Racha, Ganesh. “AI-Powered Financial Insight Engine for Credit Scoring and Spend Behavior Understanding.” International Journal of Scientific Research & Engineering Trends, vol. 10, no. 2, Mar.–Apr. 2024, pp. 1–8.
37. Racha, Ganesh. “Adaptive Quantum Blockchain for Secure IoT Resource Coordination.” International Journal of Science, Engineering and Technology, vol. 11, no. 3, 2023.
38. Nijim, M., Albataineh, H., Kanumuri, V., Goyal, A., Mishra, A., Hicks, D. (2023). Countering Cybersecurity Threats in Smart Grid Systems Using Machine Learning. In: Daimi, K., Alsadoon, A., Peoples, C., El Madhoun, N. (eds) Emerging Trends in Cybersecurity Applications. Springer, Cham. https://doi.org/10.1007/978-3-031-09640-2_14
39. Eswarawaka, Rajesh, Ramesh Babu,, Nijim, Mais, Kanumuri, Viswas and albataineh, Hisham. "Effectiveness of machine learning and deep learning in cybersecurity". Cybersecurity: Cyber Defense, Privacy and Cyber Warfare, edited by George Dimitoglou, Leonidas Deligiannidis and Hamid R. Arabnia, De Gruyter, 2025, pp. 199-214. https://doi.org/10.1515/9783111436548-009

40. Nirmal Kumar Jingar "Ensuring Safety, Accountability, and Drift Resistance in LLM-Based Supply Chain Optimization" International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Print ISSN : 2395-1990, Online ISSN : 2394-4099, Volume 10, Issue 1, pp.472-482, January-February-2023. Available at doi : https://doi.org/10.32628/IJSRSET2310372
41. Jingar, N. K. (2026, February 13). Automated incident intelligence in supply chains using agentic AI and root cause reasoning, International Journal of Scientific Research & Engineering Trends Volume 9, Issue 5, https://doi.org/10.5281/zenodo.18162511