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Original Article

Smart Anemia Diagnosis: A Non-Invasive Hemoglobin Optical Sense with AI-based WebApp for Early Detection & Prevention

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Abstract *- Monitoring blood Hemoglobin (Hb) level is crucial for diagnosis, evaluation, and treatment of various illnesses. Such illnesses can be cured at early stages by maintaining good blood health. For average humans, Hemoglobin may not hold much importance, but for anemic patients, it is the key to life. Given the vital role of Hemoglobin, there is a need for an efficient mechanism to estimate the Hb levels regularly and to detect and prevent Anemia prevalence in patients. Although the researchers have developed various models for anemia detection, none of the studies proposed the essential solutions to prevent it. This paper provides insights into a non-invasive method for monitoring Hb levels cost-effectively and providing preventive measures using an ML Algorithm. To construct the non-invasive kit, an Arduino UNO and an optical sensor MAX30105 have been put to use. Additionally, a web-based application has been designed using Streamlit Community Cloud & GitHub to aid in the early detection of anemia and provide tailored prescriptions, including numerous medicines and daily-life remedies. The performance parameters of the ML (specifically RandomForest Classifier) model are 0.9868 precision, 0.9841 recall, 0.9852 F1-score, and 0.9998 AUC-ROC score. Such accurate systems may eventually give doctors access to real-time data, facilitating quicker diagnosis and treatment. To enable reproducibility, the code developed for this research has been made openly accessible.*

Keywords *- Non-Invasive, Hemoglobin, Optical Sensor, Anemia, Streamlit, RandomForest Classifier, Machine Learning, Github, Streamlit Community Cloud.*

1. Introduction

"The journey of life begins with oxygen, and hemoglobin is the guide that leads it" is a beautiful quote to show the role of a single cell of Hemoglobin in one's life when it comes to life existence. Every living organism is dependent on oxygen to survive, and it is used for cellular respiration (the process by which cells generate energy).

During circulation of oxygen, hemoglobin proves to be a vital protein that guides oxygen to flow from lungs to various body tissues and also to flow carbon dioxide from body tissues to lungs for exhalation. Hemoglobin has a range that should always be normal or in the right proportion. The normal range of hemoglobin in blood depends on factors such as sex, age, and altitude. On such health problems, i.e., Anemia, there are various studies by several researchers. Previous research involved different optical sensors like OPT101, MAX3010, etc, while this research comprises the MAX30105 sensor, which works excellently on medical data and monitoring purposes. Many studies have showcased the use of ML Algorithms to detect Anemia; however, none of the studies are tailored to suggest preventive measures to prevent Anemia. Prior studies lacked the capability to recommend medicines or remedies to tackle Anemia. This feature of the system can be pivotal for doctors to suggest the correct solutions. In this paper, an innovative kit for hemoglobin estimation has been devised using an optical sensor and an embedded system, which leads to a cost-effective solution. A quantitative comparison between previous studies and this research study is highlighted in the following sections.

The experimental results of this hardware system show a reasonable accuracy, while the software system shows an exceptional accuracy of 98.50%. An ML model with this much accuracy, combined with a non-invasive kit, enhances the system's uniqueness and efficiency. The source code used in this study is openly accessible, with details given in the Code Availability section.

2. Literature Review

Various methods, including invasive and non-invasive approaches, have been devised for Hb level estimation. Instead of conventional or invasive methods, non-invasive hemoglobin measurement techniques such as PPG (photoplethysmography), pulse oximetry, image-based techniques, and near-infrared light offer a number of benefits [3, 4]. These techniques offer a safer, more comfortable, and pleasant alternative to checking patients' hemoglobin levels without requiring blood samples. Non-invasive devices also lower the danger of infection and cross-contamination [5]. Non-invasive devices exhibit multiple uses in the medical industry. For diabetic patients, these non-invasive kits can be vital in maintaining good health [6]. Additionally, these devices can be used during the perioperative period or during surgeries when the patient is under anaesthesia [7]. Some studies show the potential of non-invasive devices for reliable anemia screening in schools, facilitating early detection of anemia in schoolchildren [8].

The non-invasive devices consisting of the embedded systems have achieved high accuracies ranging from 85-91%. Such devices make use of optical sensors (biosensors) and near-infrared spectroscopy to estimate the Hb levels. These devices are not only portable, but also require very limited resources [1, 2, 9]. Optical devices mainly use multiple LEDs. These LEDs are designed to have various wavelengths, which may range from 650nm to 950 nm. The standardization process helps to achieve Multispectral Photoplethysmography [13]. By utilizing standardized LEDs, the accuracy of the device can be improved [10, 11]. Convolutional Neural Networks (CNNs) are a prominent non-invasive method for hemoglobin estimation. The combination of CNNs and optical sensors may result in pertinent AI-powered tools that can be utilized to improve hemoglobin measurement systems [12]. The Artificial Neural Networks (ANN) have been utilised to detect the Hemoglobin level of patients using 10-second recorded videos of fingertips. The Hb levels are estimated by using RGB spectrum analysis for 75 adults [13].

By utilising various Machine Learning algorithms and models, the detection of Anemia is achieved effortlessly. Some researchers have utilised Artificial Intelligence-Based models for the detection of anemia, analyzing medical images such as fingernails, palm, and conjunctiva (eye images) [14-16]. These images can be directly clicked on available smartphone cameras, and the detection of anemia is possible [17]. In pregnant women, iron-deficiency type anemia is prominent. This type of anemia is analyzed by the skin tone changes in the images of the conjunctiva of the eye [18].

3. Proposed Methodology

The proposed method involves two segments, one for the hardware system and the other for the software system. The hardware section involves the integration of various components in the system and the construction procedure for the hardware model. The software section provides detailed insights about the deployment of the ML model in the web-based application.

3.1. Hardware Section

3.1.1. System Design and Implementation

This section outlines a detailed system design and working for Non-Invasive Hemoglobin Estimation Kit as shown in Figure 1. Hemoglobin is comprised of protein cells which are having the property of reflecting the UV rays when exposed to it. The gadget's core lies on the Arduino UNO board for functioning. The rationale behind the selection of Arduino UNO was its lightweight and cost-effective nature. The optical sensor MAX30105 has a crucial role in ensuring the non-invasive nature of the system. Additionally, 2 UV LEDs, each of 400 nm, 1 IR LED of 770 nm, and a user interface, i.e., a 16x2 LCD screen, are present in the circuit. As depicted in Figure 1, the positioning of the UV LEDs, the finger, and the MAX30105 optical sensor in the kit is kept exactly aligned perpendicular to each other. Figure 2 is the final hardware model.

The gadget can be powered by a USB power source or a battery. Once the kit is started, the Arduino, the optical sensor, and the LCD screen start functioning. The user is advised to put a clean index finger on the touchpoint once the LCD screen shows the initialization message, as depicted in Figure 2. It is expected for the user to ensure a straight placement of his/her index finger on the touchpoint to fulfill the perpendicular alignment. The system does not operate until a finger is placed on the sensor. In order to detect human finger intervention, an additional infrared LED is fitted to the kit. The IR LED detects the presence of a finger and gives a command to switch ON the UV LEDs. Once both of the UV LEDs are powered, the light penetrates through the finger, reaching up to hemoglobin cells in no time.

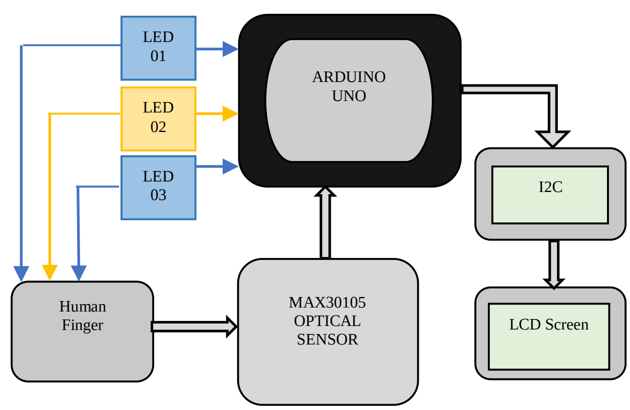

Fig. 1 Schematic diagram of non-invasive hemoglobin estimation kit

The LEDs are kept in the ON state for 5 seconds, during which the finger is expected to be kept still. The reflected UV rays from the cells are then captured by the optically sensitive segment of the MAX30105 optical sensor, structurally ensuring that only the normal rays are caught. Once this acquisition of signal is completed, the light signal is sent to the embedded system, i.e., Arduino Uno present in the kit. The Arduino uses this recorded signal to determine the absorption at various wavelengths by reading the light intensity data. To guarantee precise hemoglobin estimation, the Arduino will carry out the required calculations using preset algorithms. Hemoglobin levels are estimated using the link between hemoglobin concentration and light absorption. Next, the LCD panel shows the determined hemoglobin concentration. In addition to providing real-time hemoglobin level data, the LCD might have a graphical user interface for additional visual feedback. The hardware system is protected with a black colored polymer sheet prominently to prevent the escape of light.

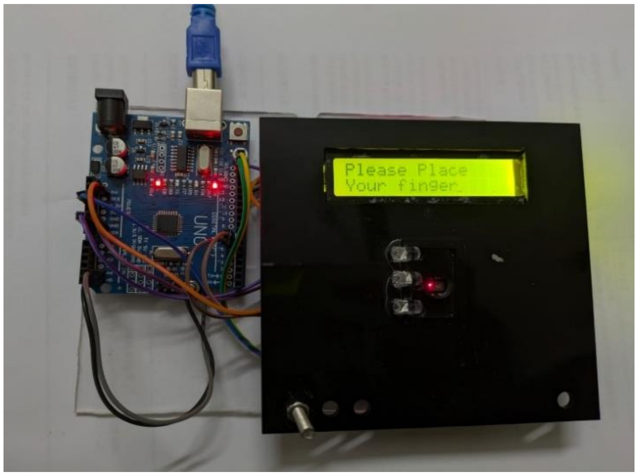

Fig. 2 Hardware prototype of the system

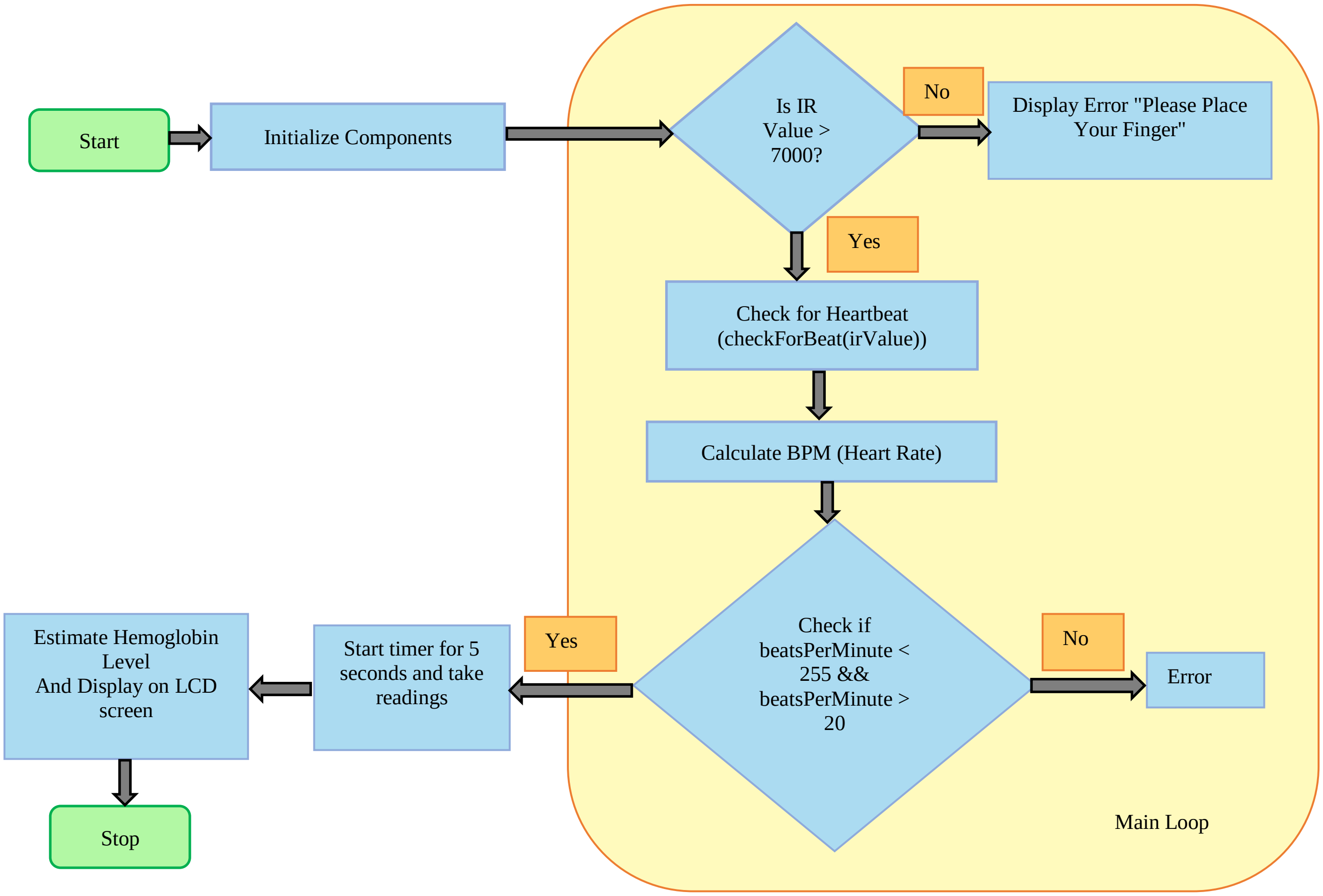

Fig. 3 Flowchart for non-invasive hemoglobin monitoring system

3.1.2. Arduino-Based Non-Invasive Hb Estimation

Figure 3 demonstrates the algorithm for the Non-Invasive Hemoglobin Monitoring System. Once powered, the system starts by initializing the components. Inside the main loop, various commands for detecting the finger, estimating heart rate, and estimating hemoglobin are implemented. Along with the change in each heartbeat, the blood circulation changes every beat. This may show uneven reading every second. So, the system is programmed to collect various readings for 5 seconds and return an average Hb value. The 16x2 LCD screen ensures a visual representation of the Hb level. The system is then ready to accept input from the next user.

4. Machine Learning

4.1. Methodology to Develop an Anemia Detection and Prevention System using Machine Learning

Figure 4 indicates the steps that are followed while performing the software section of the anemia detection and prevention system. The renowned Machine Learning algorithm, Random Forest Classifier, has been chosen for the detection of Anemia severity in patients because of its robust nature and its proven accuracy in the medical industry. To deploy the ML model, the first step was to collect intensive data from the pathological labs where patients used to come for normal routine check-ups and found out that they were Anemic patients (due to having low Hb levels below Normal Hb ranges). The dataset comprised physical parameters like age, Hb (the most important feature), gender, and weight of all the patients (gathered ~1000 samples). The dataset was loaded and preprocessed successfully, which was further used to train the model using the RandomForest Classifier model of supervised learning, best suited for medical-related complex data. The model is capable of identifying various classes of anemia severity by separating the Hemoglobin levels (Normal ranges of Hb levels are obtained from Clinical Laboratories, and anemia thresholds are obtained through WHO guidelines – anemia cut-offs – mentioned in Table 1 below) into four groups, i.e., Normal, Mild, Moderate, and Severe. According to the severity level of Anemia for each class, the prescription suggested by the model is unique. The model is equipped to prescribe the solutions for each system of medicine, including Allopathy, Ayurveda, Naturopathy, and Homeopathy (mentioned from online sources) as depicted in Table 3. Since the model encompasses every medicinal system, the doctors can effortlessly prescribe the correct remedies to the patients. Additional comments regarding daily life essentials are introduced by the model for maintaining good hemoglobin health. Further, the ML model is deployed in the web application through GitHub using Streamlit Community Cloud. For Code reference and app demo, go through the Code Availability section.

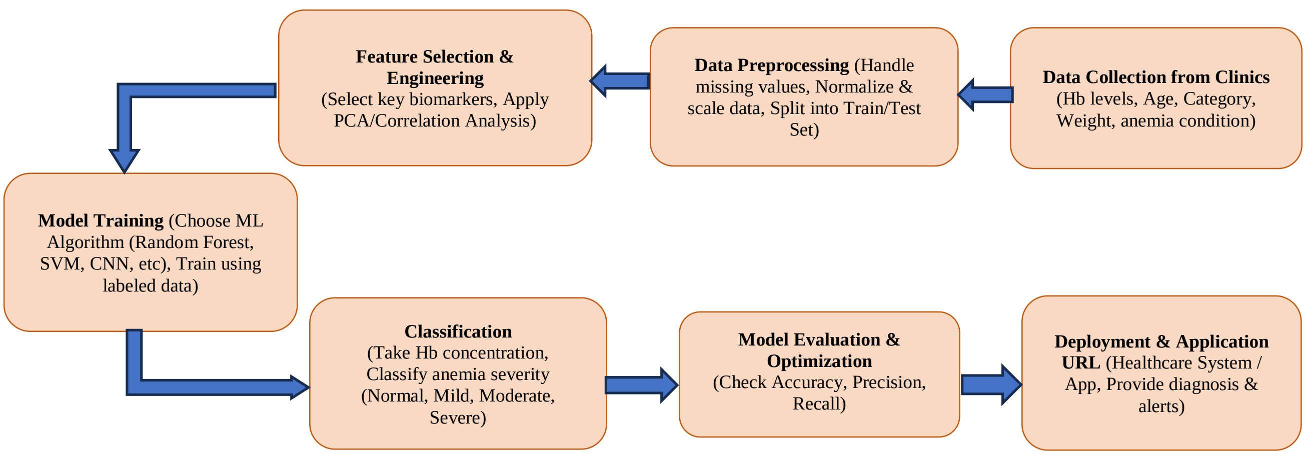

Fig. 4 Workflow of the proposed machine learning based anemia detection & prevention system

Table 1 indicates the ranges or thresholds of Hb levels referred from clinical laboratories (normal ranges) and WHO (World Health Organization) guidelines of anemia cut-offs for Mild, Moderate, and Severe anemia criteria while performing.

Table 1. Ranges or thresholds of Hb levels used during model development

Hb Levels	Men	Women (Non-Pregnant)	Pregnant Women	Children (6 months – 5 years)	Children (5–12 years)
Normal	13.0 – 17.0 g/dL	12.0 – 15.0 g/dL	11.0 – 14.0 g/dL	11.0 – 14.0 g/dL	11.5 – 15.0 g/dL
Mild	11.0 – 12.9 g/dL	11.0 – 11.9 g/dL	10.0 – 10.9 g/dL	10.0 – 10.9 g/dL	11.0 – 11.4 g/dL
Moderate	8.0 – 10.9 g/dL	8.0 – 10.9 g/dL	7.0 – 9.9 g/dL	7.0 – 9.9 g/dL	8.0 – 10.9 g/dL
Severe	< 8.0 g/dL	< 8.0 g/dL	< 7.0 g/dL	< 7.0 g/dL	< 8.0 g/dL

4.1.1. Evaluation Metrics

The anemia classification model exhibits an outstanding accuracy of 98.50% as depicted in Table 2, with minimal false positives and false negatives. Recall scores remain consistently high, with Mild and Moderate anemia cases achieving 100% recall, while Normal (0.975) and Severe (0.962) categories represent slight misclassifications. The model competently balances precision (0.986), recall (0.9841), and F1-score (0.9852), ensuring reliable anemia detection. However, slight misclassification in the Normal and Severe categories suggests room for improvement by adding more training data or refining classification thresholds.

Table 2. Evaluation metrics

	Precision	Recall	F1-score	Support
Mild	0.979592	1	0.989691	48
Moderate	0.967742	1	0.983607	60
Normal	1	0.975	0.987342	40
Severe	1	0.961538	0.980392	52
Accuracy	0.985	0.985	0.985	0.985
macro avg	0.986833	0.984135	0.985258	200
weighted avg	0.985425	0.985	0.984978	200

Figure 5 depicts a feature importance analysis in which hemoglobin (Hb)is highlighted as the most crucial factor, scoring above 0.8 in relevance and significance, confirming its direct role in anemia diagnosis. Category, representing patient classification, plays a prominent but secondary role, while age and weight contribute minimally. This confirms that Hb levels primarily determine anemia severity, with other features assisting in classification accuracy. Figure 6 shows the AUC-ROC score of 0.9998, which further confirms the model's superior predictive performance. The nearly perfect ROC curves across all classes indicate excellent differentiation ability, with a low False Positive Rate (FPR) and high True Positive Rate (TPR). The model greatly surpasses a random classifier (AUC = 0.5) and also proves its effectiveness in highlighting different anemia severity levels with minimal misclassification. Figure 7 depicts a confusion matrix generated in order to evaluate the performance of the model (Random Forest Classifier) across four classes: Normal, Mild, Moderate, Severe. From the result, it shows that the model performs excellent classification between the four classes of Anemia with very minimal misclassification (i.e, two such cases/instances were found to be misclassified). The classifier correctly identified: 48 out of 48 Normal cases (100%), 60 out of 60 Mild cases (100%), 39 out of 40 Moderate cases (97.5%), 51 out of 52 Severe cases (98.1%). Only two instances were misclassified: One Moderate case was incorrectly predicted as Normal, and One Severe case was incorrectly predicted as Mild. The high concentration of predictions along the diagonal of the matrix clearly shows that the classifier distinguishes perfectly between the four anemia severity levels. The extremely low rate of misclassification reflects the robustness of the Random Forest Classifier (model) and also its ability to capture class-specific patterns effectively.

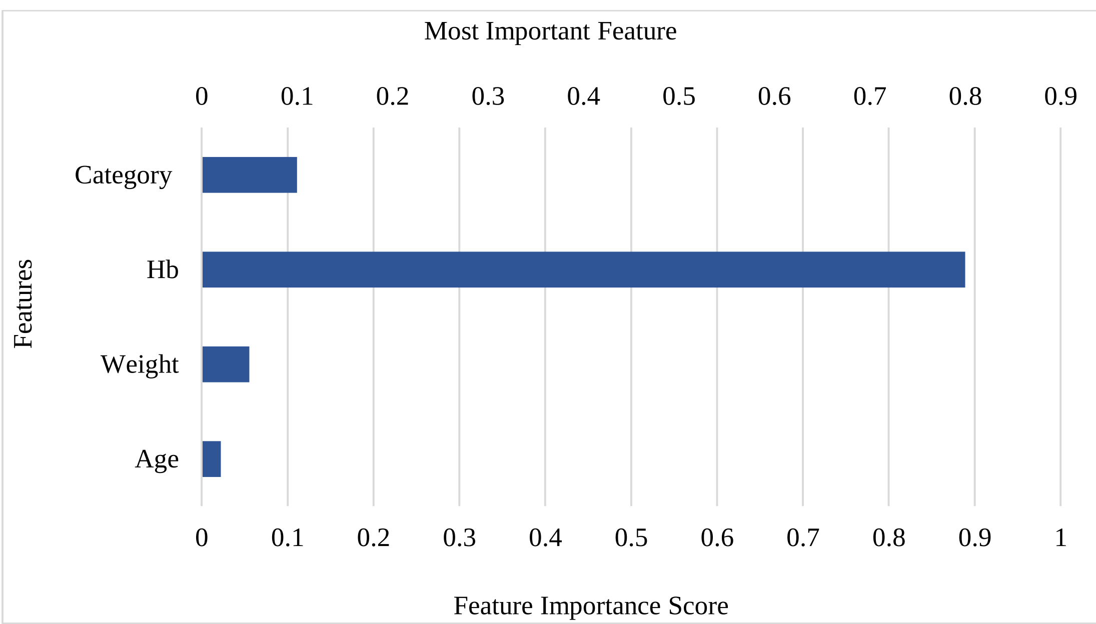

Fig. 5 Hb Vs Other physical parameters importance graph

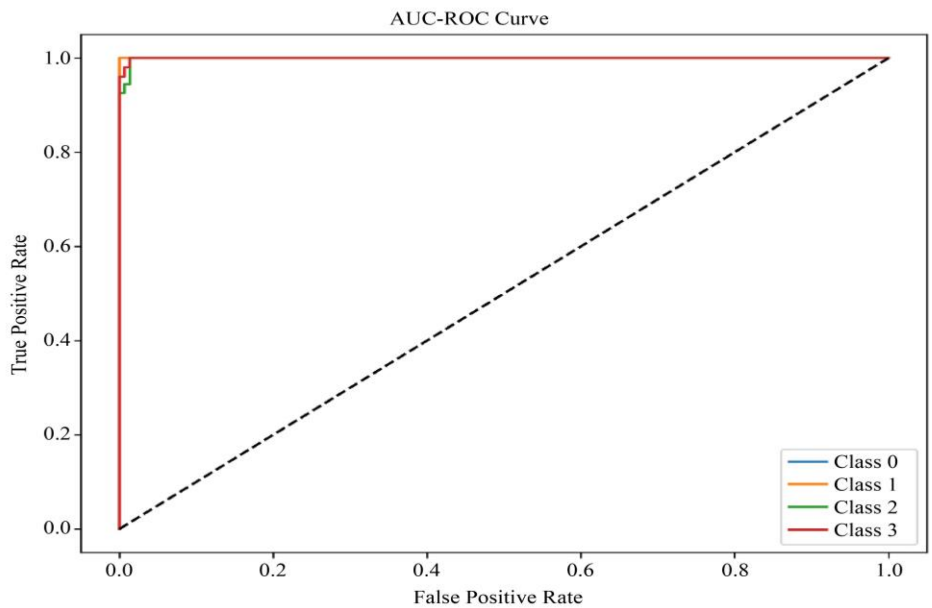

Fig. 6 AUC-ROC curve for random forest classifier

Overall, the confusion matrix confirms that the Random Forest classifier exhibits strong generalization, high accuracy, and reliable performance, making it best suited for practical applications and further deployment.

Elements in Table 3 are a partial overview of the prescribed medicines; several more medicines and remedies are revealed during actual diagnosis on the diagnosis webpage. These remedies are gathered and mentioned from various online sources. Each class provides different remedies or preventive measures for the patient on the basis of his/her anemic condition. This model also provides medicines or remedies in criteria like Allopathy, Ayurveda, Naturopathy, Homeopathy, and some general remedies that can be applied /done while being at home. So, patients can prefer any remedy in accordance with ease and free will. These remedies are safe as written, based on detailed and thorough research.

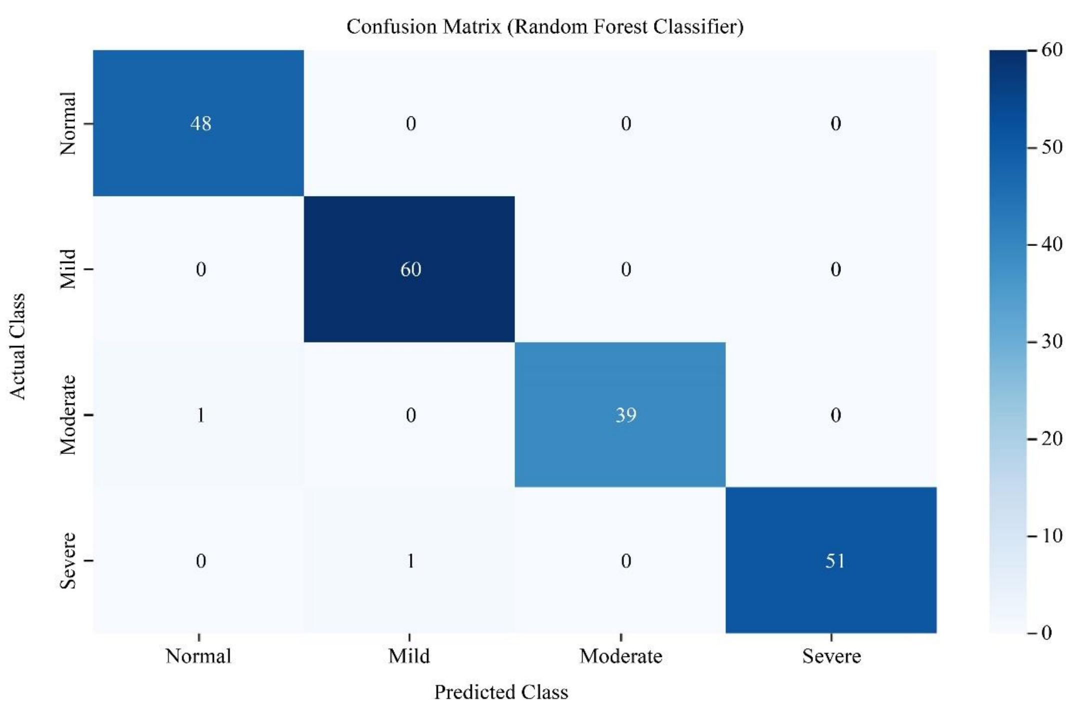

Fig. 7 Confusion matrix (random forest classifier)

Table 3. Anemia severity classification and prescription suggested by the model for each classification

Anemia Severity	Allopathy	Ayurveda	Naturopathy	Homeopathy	Comments
Normal	Not required	Chyawanprash	Beetroot juice	Ferrum Phosphoricum	Stay hydrated
Mild	Ferrous Sulfate tablets	Ashwagandha	Pomegranate juice	Natrum Muriaticum 30C	Avoid tea/coffee after meals
Moderate	Vitamin B12 injections (Cyanocobalamin)	Punarnava Mandur tablets	Green smoothies	China Officinalis 30C	Avoid excess alcohol consumption
Severe	Iron Sucrose IV infusion	Draksharishta (grape-based iron tonic)	Fresh Aloe Vera juice	Ferrum Metallicum 30C	Seek immediate medical attention

4.1.2. Anemia Detection and Prevention WebApp using Streamlit

Using Streamlit, a web application is designed for anemia detection and prevention. The web application is named Anemia Shield. The proposed anemia detection and prevention system is implemented by utilizing Python's Streamlit library to create an interactive, browser-based interface. The web application comprises an error-handling and refresh mechanism to increase the efficiency of the model.

The app has been hosted on the Streamlit Community Cloud and is deployed by running the app locally on the computer. At the beginning, the new user needs to register on the website, and the Admin has to approve the new entry. The authentication is secured through SHA-256 password hashing. Figure 8 depicts the User Authentication Page, where the user can log in or register.

When the user is finally logged in, a Home screen appears as depicted in Figure 9, which includes the app information and a side panel. For Anemia diagnosis, the user is expected to click on the Diagnosis option. After the diagnosis, the user can log out of the system by using a logout function. The diagnosis page, shown in Figure 10, is designed to provide immediate and clear insights into a patient's anaemic condition. The patient is advised to fill in the data of his/her name, age, gender, weight, and hemoglobin level, and consecutively hit the Detect Anemia button to start the diagnosis.

When patients input their details, including hemoglobin levels, the system quickly classifies the severity of anemia and offers specific preventive measures. In this case, a female subject has provided the required data and is found to be moderately anaemic. The prescription in this case includes all the suggestions from various medical domains like allopathy, homeopathy, ayurveda, and naturopathy.

This feature enables the coverage of various medical domains in one. This personalized feedback not only informs the user of their current state but also guides them on potential dietary or medical interventions. The intuitive layout and real-time analysis ensure that the page serves as an effective first point of contact for anemia diagnosis.

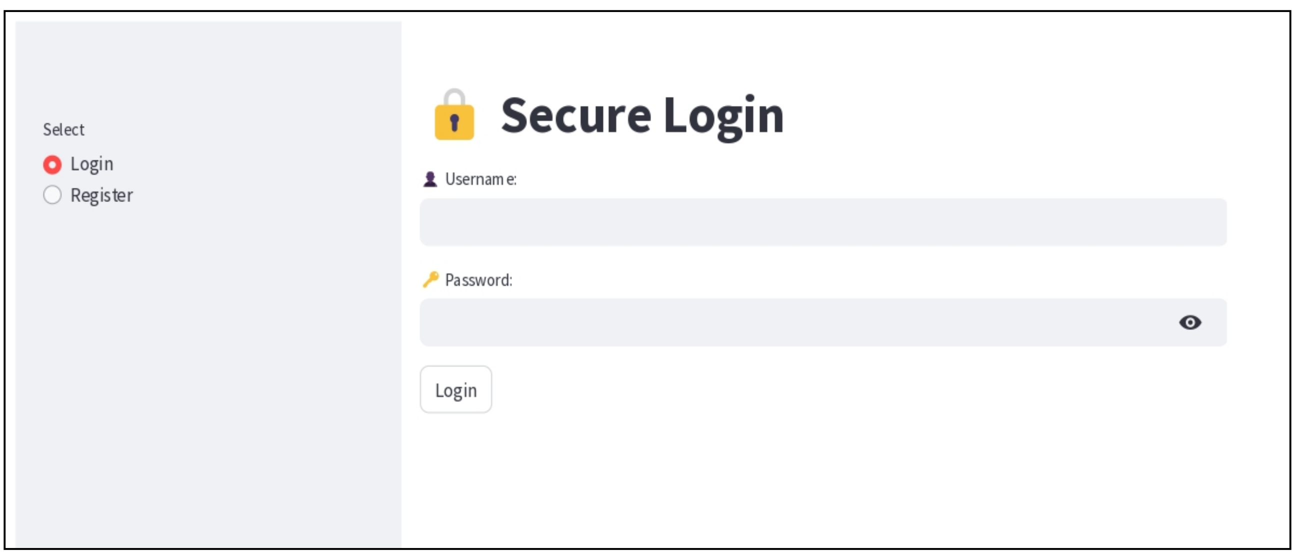

Fig. 8 User authentication page

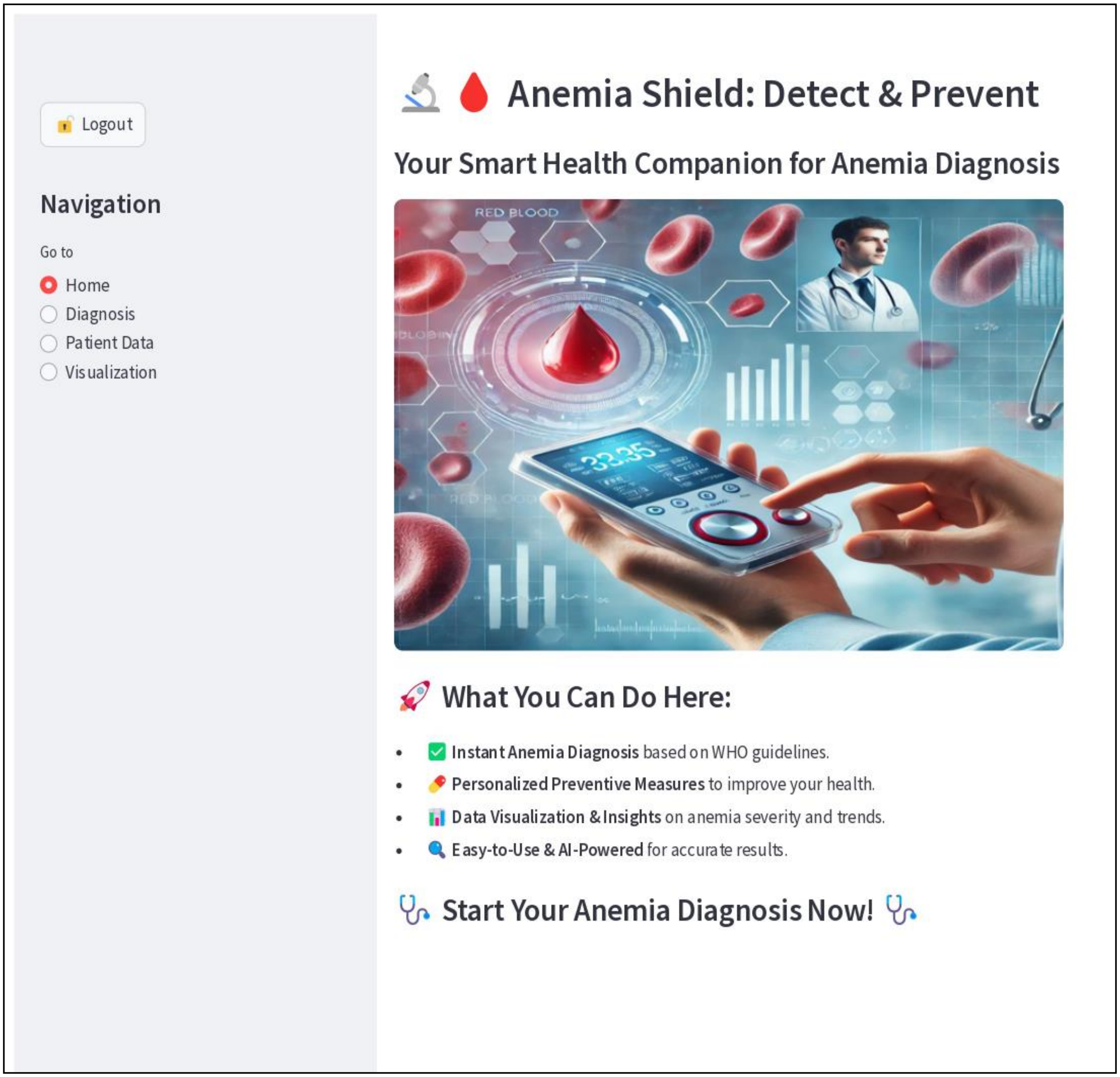

Fig. 9 Home page of web-app

The patient data records page (Figure 11) consolidates all diagnostic results into a well-organized table, making it easy to review and track individual cases over time.

It plays a crucial role in monitoring patient histories and observing trends in anemia severity across different demographics.

By having all records in one place, healthcare professionals can efficiently follow up on past diagnoses and adjust treatment plans as necessary. This systematic record-keeping supports both clinical practice and research initiatives. Have the ability to store as many patients as possible. Figure 12 demonstrates an anemia distribution graph page, which offers a visual summary of the overall prevalence of various anemia conditions among the patient cohort. Displayed as a pie chart, the graph immediately highlights the proportion of normal, mild, moderate, and severe cases. This visual tool simplifies data interpretation and helps identify critical areas requiring intervention. The clear representation of trends not only reinforces the statistical findings but also aids in strategic planning for targeted healthcare measures, and is useful to know the condition and trends that people are facing.

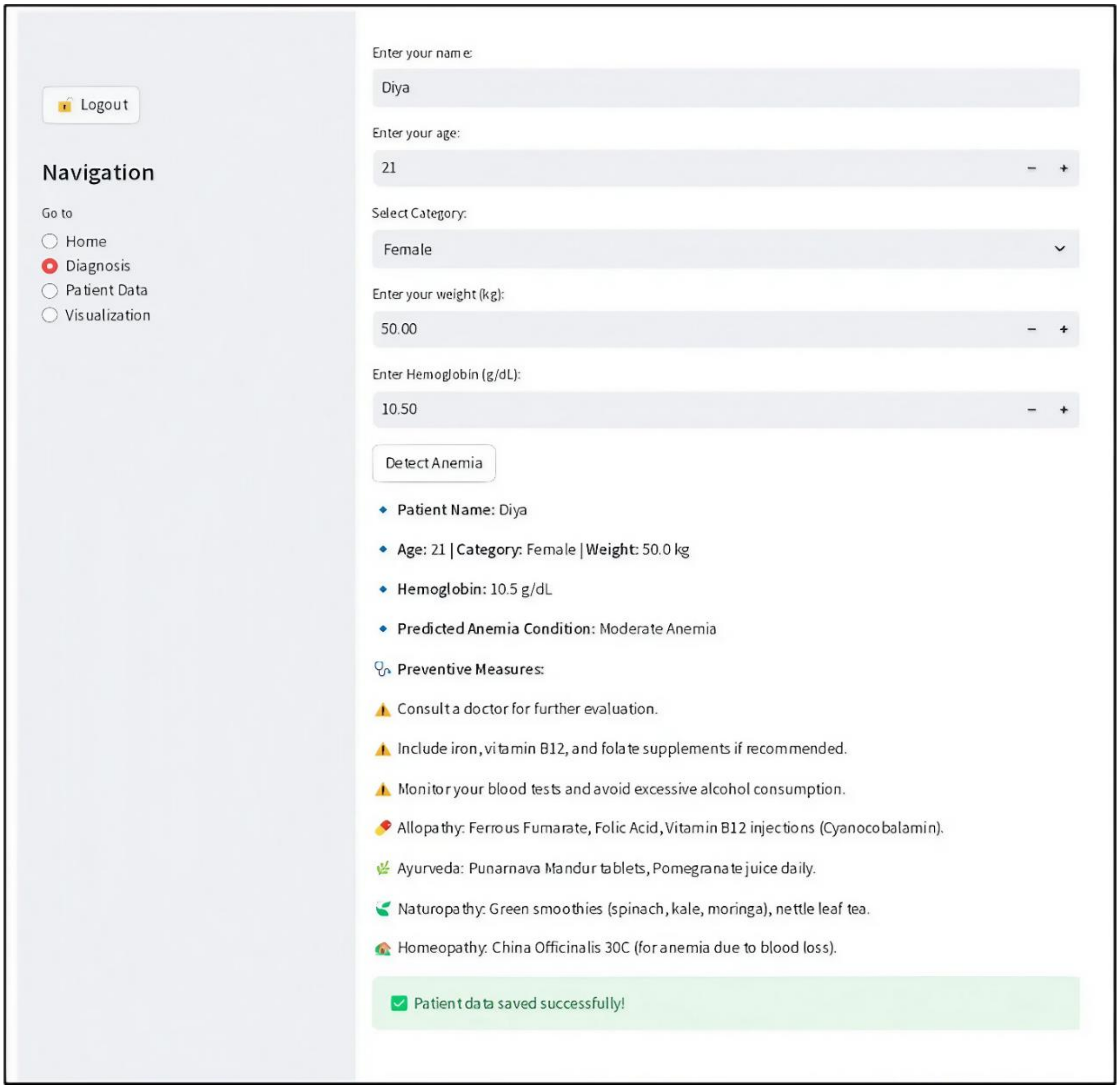

Fig. 10 Diagnosis page & preventive measures suggestion for a patient

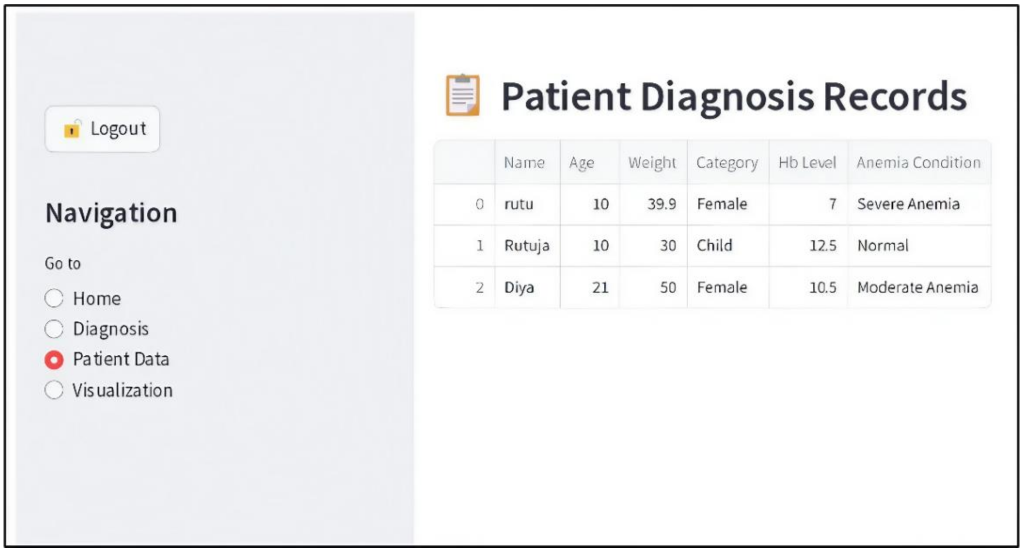

Fig. 11 Patient diagnosis records page

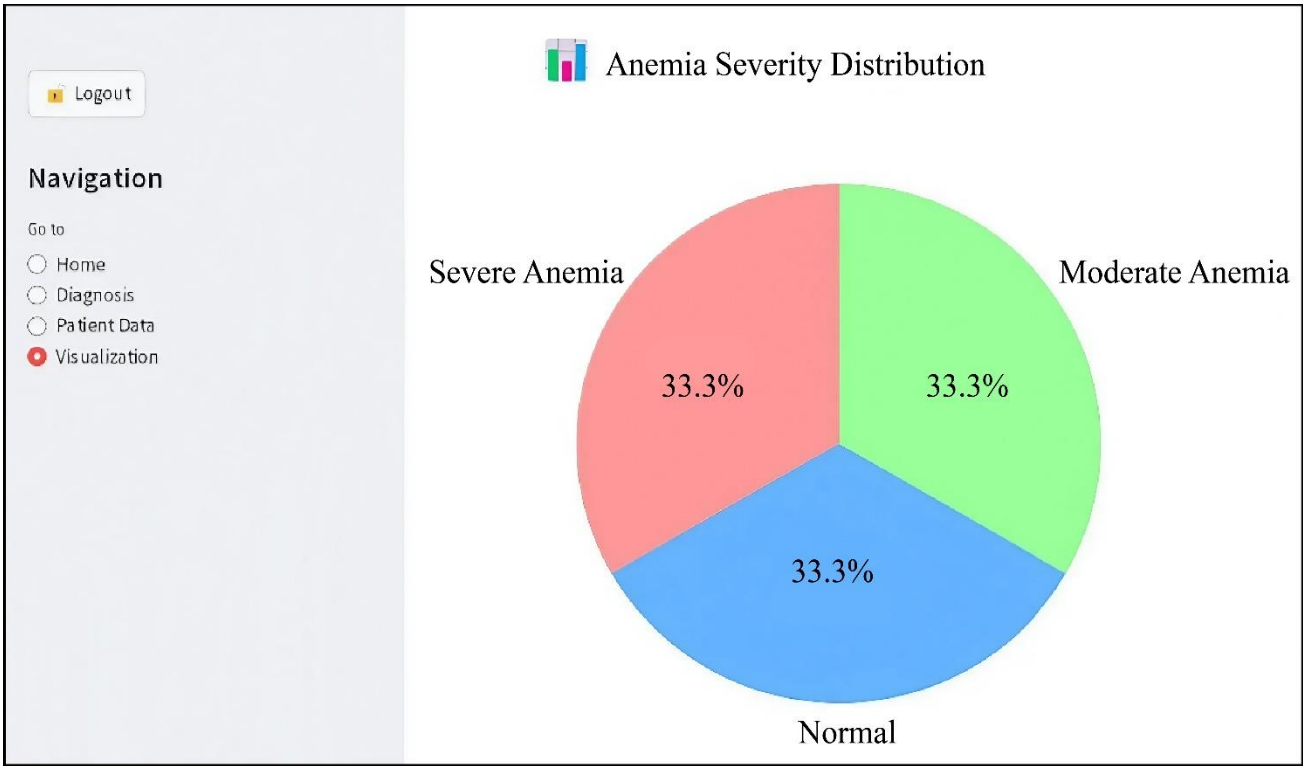

Fig. 12 Anemia severity distribution chart

5. Results and Discussion

Figure 13 indicates a normal hemoglobin concentration of a person under test. The estimated hemoglobin level of the female patient in this case is 11.79 g/dL. This value is merely an estimate of the patient's hemoglobin level.

This outcome was obtained by the precise optical sensor and the Arduino-based system's real-time processing capabilities. With a hemoglobin level of 11.79 g/dL, the female individual has a slightly lower Hb concentration, which is normally between 12 and 15 g/dL for female adults and ranges from 13.5 to 17.5 for male adults.

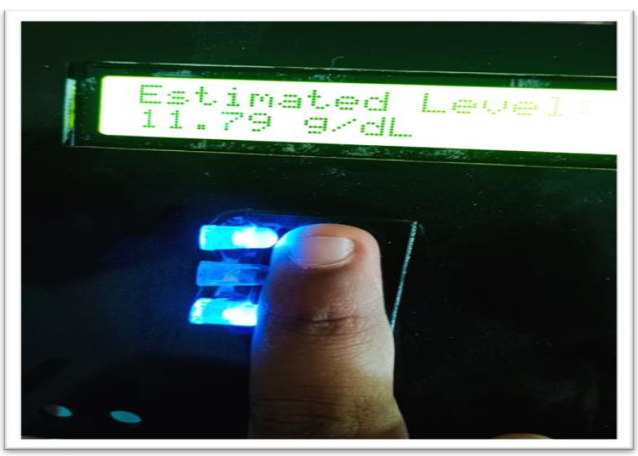

Fig. 13 Estimated hemoglobin level of a patient

To check the reliability and accuracy of the Hemoglobin Estimation Kit, the team has intensively collected patient data from the affiliated Medical Centre. Informed consent was duly obtained from the patients as well as the doctor to initiate the process and further analyze the data.

The patients were asked to coordinate with the team, and using the Hemoglobin Estimation Kit, their Hb levels were estimated. As listed in Table 4 below, a total of 25 patients were examined. The records in Table 4 show a minimum difference of 0.2 and a maximum difference of 2.5 in certain readings.

The mean absolute error of the estimated values observed by the system is found to be 0.6562. Additionally, clinical Pathology tests were done on the same subjects for analysis purposes. The graph (Figure 14) below shows the comparison between Pathology Tested Hb and the Hemoglobin level estimated through the kit.

Furthermore, the level of Hemoglobin of the subject can be affected by various factors like skin texture, skin color, age, gender, the position of the finger, the light intensity in the outside environment, the accuracy of the code, loose wiring in the system, etc. Besides the factors like pregnancy and gender of the patient, the Hemoglobin level can also vary depending on lifestyle habits and the altitude of the region. Smoking and various medical conditions (including Anemia) may affect the Hb level.

Table 4. Collected hemoglobin data for true and estimated Hb levels

Subjects	Gender	Age	Pathology Lab Tested Hb	Estimated Hb through kit	Difference
1	F	62	11.9	10.33	1.57
2	M	61	13.3	13.13	0.17
3	F	63	12.1	10.22	1.88
4	M	69	15.8	13.3	2.5
5	M	56	14	13.7	0.3
6	F	62	13	12.4	0.6
7	F	62	12.2	11.25	0.95
8	F	75	13.5	12.75	0.75
9	F	64	12.5	12.65	-0.15
10	M	60	13.5	11.7	1.8
11	F	60	13	12.48	0.52
12	F	60	12	11.66	0.34
13	F	75	14.3	14	0.3
14	M	19	15.6	15.3	0.3
15	F	21	13.4	13.1	0.3
16	F	21	12.8	12.6	0.2
17	F	21	13	11.25	1.75
18	M	25	17.3	17	0.3
19	M	19	15.4	14.2	1.2
20	M	22	15	14.82	0.18
21	F	21	12.5	11.73	0.77
22	F	62	13.4	12.11	1.29
23	M	72	14.9	14	0.9
24	M	70	15.2	14.87	0.33
25	M	82	15.1	15.33	-0.23

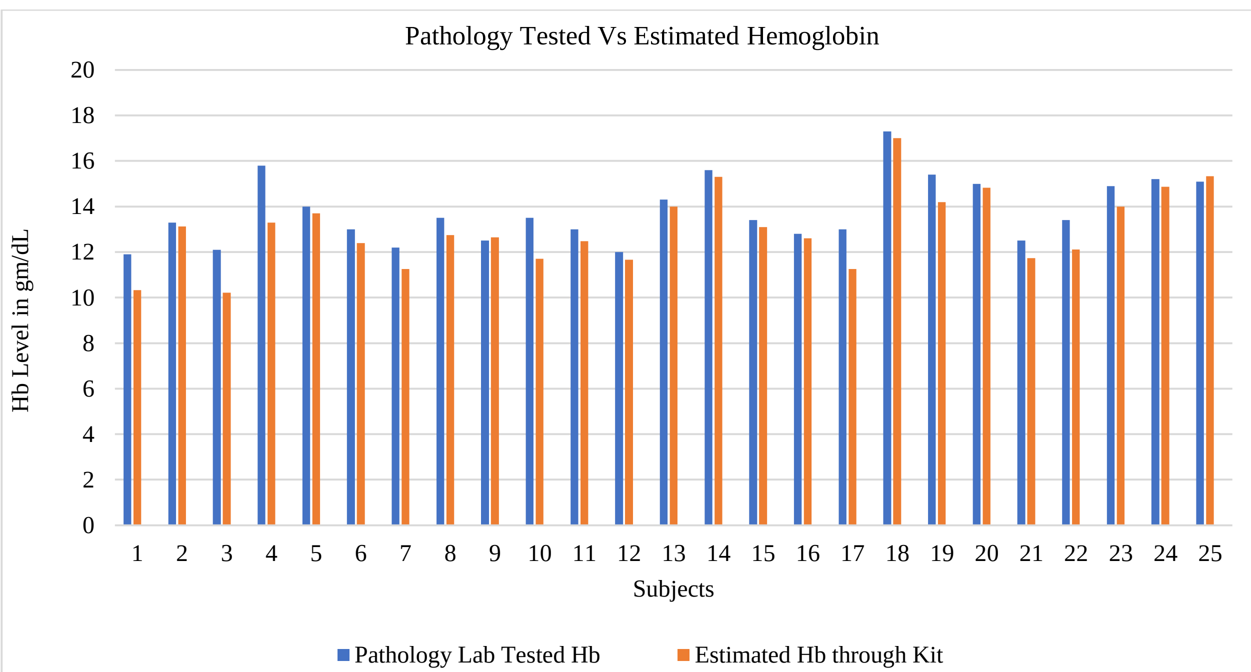

Fig. 14 Pathology-tested Hb vs Estimated Hb through

The results of preventive measures recommended by the ML model are depicted in Figure 10. The model exhibits the capability of providing tailored prescriptions according to the patient's gender and his/her anemia severity class. The system can store the patient's data, such as name, age, hemoglobin value, and diagnosis result, which are retained and can be saved for future retrieval or visualization (Figure 11). The Anemia Severity Distribution Chart Figure. 12 highlights the percentage of patients having normal, moderate, and severe anemia. Previous works are stated in Table 5. presents a comparative analysis of various machine learning models employed in previous studies alongside the current work. It highlights the performance metrics, including Precision, Recall, F1-Score, AUC-ROC, and Accuracy. Among the referenced studies, both CNN and RF models have shown competitive performance. For instance, the model proposed in [15] achieved an accuracy of 98.3% with a high F1-score of 0.9754, while [20] reported 98.4% accuracy using RF, showcasing its effectiveness in anemia-related predictions. However, from the above comparison of several methods, the current work demonstrates notable improvement across nearly all metrics. The model showed a reported accuracy of 98.50%, and it showed better results in Precision (0.9868), Recall (0.9841), F1-Score (0.9852), and AUC-ROC (0.9998). The Random Forest model implemented here outperforms prior works, additionally prescribing preventive measures and medicinal remedies for balancing hemoglobin health. One of the key factors contributing to the high accuracy of the model lies in the extensive training of the model on a large dataset. Selecting Random Forest has significantly shaped the results because of its robust nature. The category-specific Hb levels have differentiated thresholds for various categories, like male, female, children, and pregnant women. The thresholds are set according to predefined WHO-validated ranges, unlike some of the models below. This categorization has helped attain a higher precision score for this model. An exceptional AUC-ROC score of 0.9998 is triggered by the excellent class separation ability of this model.This RF model not only categorizes Anemia but also provides the prescription, which contributes highly to the authenticity of the model. None of the previous works were focused on providing solutions for safeguarding patient health, but rather were focused on anemia detection. This model shows overall high performance in every aspect of Anemia Diagnosis. The model is designed to provide the best medical suggestions to deliver interpretable clinical decisions. This feature is profoundly beneficial for healthcare practitioners or doctors to offer good measures to the patients. This model has been crafted from doctors' as well as patients' point of view, which makes it unique as compared to any other model listed below.

Table 5. Comparison of anemia detection models of previous studies and this work

Reference	Algorithm with the Highest Accuracy	Precision	Recall	F1-Score	AUC-ROC Curve	Accuracy
[14]	RF	0.804	0.822	0.807	0.782	82.2%
[15]	CNN	0.9764	0.9744	0.9754	0.9993	98.3%
[19]	CNN	0.95	0.96	-	0.99	96%
[20]	RF	0.981	0.988	0.985	0.979	98.4%
This work	RF (Classifier)	0.9868	0.9841	0.9852	0.9998	98.5%

6. Conclusion

In the field of Medical Diagnostics, the Hemoglobin Estimation kit can be proven as a useful gadget due to its capability of estimating Hb levels in just 5 seconds, being time-efficient for the patients and the doctors. Where the conventional blood tests take 24 hours or multiple days to obtain the results, this kit shows the Hb levels within seconds.

The hardware system possessed a reasonable accuracy in estimating hemoglobin with a mean absolute error of 0.6562. In addition, it exhibits an affordable and compact nature. The non-intrusive approach further makes it painless and convenient, especially for Anaemic patients.

Additionally, this research presents a promising approach for anemia detection, utilizing a Random Forest classifier with a notable accuracy of 98.50%. The web application provides real-time diagnosis and personalized preventive remedies, making it a practical tool for enhancing clinical decision-making.

Such systems not only save time but also are capable of storing patient history securely, which is beneficial to doctors in many ways. Machine Learning nowadays is impacting health departments in a great way; thus, the developed Web-based App (Anemia Shield: Detect & Prevent) contributes prominently towards advanced systems for the prevention of blood-related disorders like anemia.

As compared to other systems, the hardware system lacks in terms of the accuracy of Hemoglobin estimation. However, in relation to Anemia detection, the Machine Learning model in the above research leads to all the results reported in previous studies.

The above system collectively exhibits significant advantages over other methods for anemia detection, with additional features including the suggestion of medical prescription, patient diagnosis history, and the anemia severity distribution chart.

Code Availability

The implementation code, dataset, and other source files of the proposed Anemia Detection & Prevention System are available on the GitHub repository using the link: https://github.com/RutujaS-2110/Project_01_ML_Hemoglobin_Anemia_Diagnosis_and_Prevention

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