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Machine Learning Based Blood Test Parameters Estimator

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***Abstract*— This paper presents existing approaches for blood test parameters estimation. The proposed machine learning approach for estimation of diseases and preventive measures from the blood test parameters is described in this paper. The details of the interface designed for the evaluation of the proposed machine learning approach for estimation of diseases and preventive measures are presented. The results and evaluations of the proposed approach are presented. A graphical user interface is designed to evaluate the proposed approach. Anemia, Bleeding, Hyperlipidemia, Disruption of blood production, Hematological disorder, Iron poisoning, Dehydration, Infection, Vitamin deficiency, Viral disease, Diseases of the biliary tract, Heart diseases, Blood disease, Liver disease, Kidney disease, Iron deficiency, Muscle diseases, Lung disease, Overactive thyroid gland, Adult diabetes, Cancer, and Malnutrition these disease can be estimated by the proposed approach along with their preventive measures. The overall accuracy of the proposed system is 89.24%.**

***Index Terms*— blood diseases, blood parameters, disease estimator, machine learning, preventive measures estimation.**

I. INTRODUCTION

[Jishnu and Anoop, 2023] proposed a simple magnetic-based measurement system to estimate two important parameters such as heart rate and respiration. Using the magnetic plethysmography concept, the head sensor is designed to receive biosignals of the human arm, such as the radial artery. Additionally, efficient electronics and signal processor stages are designed for accurate heart rate and respiration estimation. Electronic equipment has been developed to include new levels, improved equipment (to reduce false positives and biases) and envelope testing accuracy (to estimate the cost of breathing).

[Yu et al., 2002] explored the application of signal processing methods for deducing the operational characteristics of left ventricular assist devices (LVADs). Consisting of bulk resistive, capacitive and inductive components and a time-varying capacitor, the model estimates the time pressure of the device using volumetric

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signals originating from the device. The model's parameters are not derived by aligning them with experimental data from the lab through the application of the least squares technique.
A method to iteratively estimate the system arterial bed pattern without controlling an electrically actuated total artificial heart (TAH) was developed and tested [Ruchti and Brown, 2002]. These measurements have physiological significance and are estimated from noninvasive measurements of systolic aortic flow and pressure. The efficacy of the predictive algorithm underwent evaluation using datasets derived from a pair of distinct organ systems, employing dog models in the process.
For convenient and flexible models of blood flow or perfusion in skeletal muscle with PET or radiopharmaceuticals using H215O as a tracer [Ruotsalainen et al., 2006] introduced a new stochastic two-block-two constant with two new measurement equations. The stochastic two-part two constant value model uses the hypothesis to describe changes in muscle mass and obtains a stochastic constant value distribution for each volume in the tissue.
Recursive least squares (RLS) developed a prediction method to analyze metabolic properties of the human glucose-insulin system [Neatpisarnvanit and Boston, 2002]. The plan is a method based on a non-linear mathematical model to calculate blood sugar and insulin levels in response to external glucose. [Chen et al., 2010] carefully examined the impact of signal quality on the accuracy of carbon dioxide (CO) estimation from blood pressure (ABP) using data from the MIMIC II database. Thermodilution CO (TCO) was used as the base. A total of 121 documents and 1,497 TCO measures were used. Six summation parameters and systolic area CO estimates were examined using ABP features and reliable heart rate (HR) estimates. Calculation of signal quality parameters for ABP and HR using previously described parametersr.
Predicting hypoglycemia can prevent serious health problems for people with type I insulin-dependent diabetes (IDDM). [Ghevondian et al., 2002] describe the development of a fuzzy neural network prediction algorithm (FNNE) to predict blood glucose levels in humans by modeling changes in heart rate and blood pressure, muscle impedance parameters. [Bakouri et al., 2015] introduced an innovative sliding mode controller (SMC). This controller adjusts the electrical pulse width to operate the pump, representing a new tactic in clinical control strategies. This control mechanism harnesses feedback from the estimator's forecasted input variable values. Utilizing the lumped parameter model for the cardiovascular system in tandem with the corresponding pump model, the controller's functionality is meticulously assessed via in silico trials.
Blood and blood viscosity have recently been identified as risk factors for atherothrombotic vascular disease. On the other hand, viscosity parameters must also be monitored to control blood fluidity in the treatment of some heart diseases. [Cohen-Bacrie, 2002] introduced the use of ultrasound to perform this analysis in a non-invasive manner and proposed a method to measure blood viscosity. The prediction process is developed in a more comprehensive framework and simultaneously calculates viscosity and pressure gradients based on blood distribution information..
[Tyrrell et al., 2007] presents the modeling of intricate vascular structures in 3-D imagery through cylindrical hyperellipsoids, complemented by sturdy estimation and search methodologies for image examination. This approach yields a low-fidelity representation that facilitates the amalgamation of perimeters, central trajectories, and local pose estimations. It lays out a geometric blueprint for navigational vessel passage and gleans topological data, pinpointing junction points and their interlinkages.
[Hassouna and Farag, 2005] was proposed to extract 3-dimensional vascular (TOF) magnetic resonance angiography (MRA) data from time-of-flight (TOF). The voxels of the dataset are classified as vessels or background noise. The volumetric proof is modeled with two stochastic processes. In pancreatic disease (AP), a continuous glucose monitor (CGM) is used to calculate the amount of insulin needed for an insulin pump to regulate elevated glucose concentrations in individuals with type 1 diabetes (T1D). Prompt and precise assessment of plasma insulin levels can guide in determining the appropriate insulin dosage, thereby averting the risk of hypoglycemia caused by an overdose of insulin. A technique outlined by [Hajizadeh et al., 2017] employs mathematical models to forecast plasma insulin concentration (PIC) in real-time, utilizing continuous glucose monitoring (CGM) and actual insulin data. Thirteen data sets from nine individuals with type 1 diabetes (T1D) were meticulously tracked. This monitoring employed insulin infusion site warmers (IISWD) in seven instances, while in six, they were not used, all within the bounds of two normoglycemic clamp procedures.
During heart surgeries, the utilization of cardiopulmonary bypass (CPB) triggers an inflammatory response, the intensity of which is closely linked to the patient's recovery trajectory. Typically, disease indicators are gauged through standard blood tests, which reflect gradual alterations. Yet, red blood cell (RBC) clusters, detectable via ultrasound, emerge as a signpost of inflammation, potentially guiding nursing interventions. Despite this, the correlation between such inflammatory indicators and the congregation of RBCs amidst CPB remains enigmatic. In the study by [Cloutier et al., 2011] a group of seven swine was subjected to a 90-minute cardiopulmonary

bypass (CPB) and a subsequent 120-minute reperfusion period. To intensify discomfort, four of these pigs (classified as the LPS group) received doses of lipopolysaccharide (LPS) both 24 hours prior to and immediately preceding the CPB procedure.
Hyperglycemia manifests as a persistent health condition stemming from sustained elevated glucose levels in the bloodstream. Individuals with diabetes have an increased propensity for encountering complications like cardiac conditions, kidney failure, stroke, and nerve damage. In the first stage, a prediction model founded on machine learning principles [Ramyea et al., 2022] was proposed to achieve the prediction goal. The data is not sufficient for prediction and sometimes difficulties arise in building the correct model. By harnessing the power of prediction, it's possible to mitigate the risk and severity associated with hyperglycemic conditions.

II. Proposed Machine Learning based Blood Test Parameters Estimator

In As specified in the previous section there are various existing approaches for blood test parameters estimation. Most of these approaches are not utilizing the existing technologies. These reviewed approaches are out dated. In the proposed research work following dataset features and blood test parameters are employed to gauge the patient's health status by analyzing the parameters from blood tests.
The features patient name, patient ID, gender, country, and region are utilized to uniquely identify the patient record from the dataset. While the remaining features namely Age, WBC, Neut(%), Lymph(%), RBC, HCT(%), Urea, Hb, Creatinine, Iron, HDL, and Alkaline Phosphatase are utilized to estimate the disease and recommend the certain preventive measures to the patient.
WBC: WBCs, or White Blood Cells, commonly referred to as leukocytes, serve as the body's foremost guardians against ailments and infections. Imagine them as the soldiers of your immune system, always ready for battle. They patrol the bloodstream, combating viruses, bacteria, and other harmful invaders that pose a threat to your health. The usual concentration of WBCs circulating in the bloodstream spans between 4,500 and 11,000 per microliter (equivalent to 4.5 to 11.0 × 10^9/L). It's worth noting that these values may slightly differ across various laboratories due to different measurement standards or specimen testing methods.
Neut (%): Neutrophils, a variant of leukocytes or white blood cells, act as the vanguard of the immune system's defense forces. The white blood cell family is divided into three main types: granulocytes, lymphocytes, and monocytes. Neutrophils, along with eosinophils and basophils, are part of the granulocyte group. The absolute neutrophil count is a measure of the number of neutrophils present in a blood sample. In a healthy adult, the standard range for neutrophil levels is between 2,500 and 7,000 per microliter of blood. The distribution of various white blood cell categories is delineated below: Neutrophils account for 40% to 60%, Lymphocytes for 20% to 40%, and Monocytes for 2% to 8% of all white cells.
Lymph (%): Lymphocytes, a specialized subset of white blood cells, are integral to the immune system's arsenal. They manifest in two principal varieties: B cells and T cells. B cells function as the immune system's protein production hubs, crafting antibodies to fend off intrusive pathogens such as bacteria, viruses, and toxins. For adults, the normal lymphocyte tally oscillates between 1,000 and 4,800 per microliter of blood, while children often exhibit a count of 3,000 to 9,500 lymphocytes per microliter. Lymphocytes constitute approximately 20% to 40% of the total white blood cell population.
Monocytes: Monocytes, a variety of white blood cell, are key players in your immune system. When harmful germs or bacteria infiltrate your body, monocytes transform into macrophages or dendritic cells. These cells either annihilate the intruder or signal other blood cells to join the fight, thereby preventing infection. The percentage of Monocytes is calculated automatically based on the percentages of Neut (%) and Lymph (%). In a healthy adult, the normal range for monocyte levels is between 2% and 8% of the total white blood cell count. This equates to about 200 to 800 monocytes per microliter of blood. A deviation from the normal monocyte count range may suggest the possibility of a condition associated with monocytes.
RBC: Erythrocytes, also known as red blood cells (RBC), are the lifeblood of the body's circulatory system. These specialized cells are essential for distributing important gases and nutrients within the human body. Their unique form and architecture allow them to fulfill their critical functions. The standard range for red blood cell count in adult males is about 4.35 to 5.65 million cells per microliter (mcL) of blood. In contrast, adult females typically have a range of 3.92 to 5.13 million cells per mcL of blood. In children, what is considered a high count can vary based on age and gender.
HCT (%): Hematocrit represents the volume percentage of RBC in your blood. Envision your blood as a blend of red blood cells, white blood cells, and platelets, all suspended in a plasma solution. Together, these elements constitute roughly 45% of the total volume of our blood, although the exact proportions can fluctuate. For men, the normal hematocrit levels are typically between 40% and 54%, and for women, they range from 36% to 48%.

These percentages can be determined through direct measurement with microhematocrit centrifugation or through indirect calculation methods.

Urea: Urea nitrogen, a byproduct that your kidneys filter out from your blood, is a key indicator of kidney health. Elevated Blood Urea Nitrogen (BUN) levels could suggest that your kidneys may not be functioning optimally. Early stages of kidney disease often go unnoticed as they may not present any symptoms. A BUN test is valuable for identifying kidney problems early on, when treatments are likely to be the most beneficial. The normal range for urea nitrogen levels in blood or serum is typically 5 to 20 mg/dl, which is equivalent to 1.8 to 7.1 mmol of urea per lite. The spectrum of urea nitrogen values spans wide, a tapestry woven by the diverse threads of dietary protein intake, the body's own protein metabolism, the ebb and flow of hydration, the liver's diligent urea crafting, and the kidneys' meticulous filtration dance.

Hb: Hemoglobin, the oxygen-carrying superstar of our blood, needs to be present in adequate levels to ensure proper oxygen delivery to our tissues. Hemoglobin levels in our blood are gauged in units of grams per deciliter (g/dl). For men, a healthy hemoglobin level falls between 14 to 18 g/dl, while for women, it's typically between 12 to 16 g/dl. If the hemoglobin level dips below these ranges, it's a sign of anemia.

Creatinine: Creatinine is a byproduct of creatine, a compound that the body produces and uses primarily to fuel muscles. A test for creatinine is conducted to assess the functionality of your kidneys, as they are responsible for completely eliminating creatinine from the body. The usual creatinine concentration spans from 0.7 to 1.3 mg/dL (61.9 to 114.9 µmol/L) for men and 0.6 to 1.1 mg/dL (53 to 97.2 µmol/L) for women. This variance reflects the generally smaller muscle mass in women, which often results in lower creatinine levels compared to men.

Iron: Around 70% of the body's iron is contained within hemoglobin, the protein in red blood cells responsible for oxygen transport. Iron is vital for hemoglobin synthesis. Iron and Total Iron-Binding Capacity (TIBC) are measured in micrograms per deciliter (mcg/dL), with normal iron ranges being 70 to 175 mcg/dL for men and 50 to 170 mcg/dL for women.

HDL: High-density lipoprotein cholesterol, commonly known as HDL, is frequently referred to as the "good" cholesterol. Picture it as a diligent cleaner in your bloodstream, gathering cholesterol and ferrying it back to the liver for disposal. Elevated HDL cholesterol levels are associated with a reduced risk of developing heart disease and stroke. Here are some key cholesterol levels to keep in mind: Aim for total cholesterol under 200 mg/dL (5.2 mmol/L), LDL cholesterol under 130 mg/dL (3.4 mmol/L), and HDL cholesterol over 40 mg/dL (1 mmol/L) for men and over 50 mg/dL (1.3 mmol/L) for women.

Alkaline Phosphatase: Alkaline phosphatases (ALPs) are a collection of isoenzymes that reside on the outermost layer of the cell membrane. They play a pivotal role in catalyzing the breakdown of organic phosphate esters located in the extracellular space. This process is heavily reliant on the presence of essential cofactors, namely zinc and magnesium. The common range for this enzyme's concentration is 44 to 147 IU/L (international units per liter) or 0.73 to 2.45 µkat/L (microkatal per liter). It's noteworthy that these reference values may differ slightly from one laboratory to another. Furthermore, these values can also vary based on factors such as age and gender.

For analyzing the patient health condition on the current health parameters the questionnaire is displayed to the patient comprising following questions:

Do you smoke?
Are you pregnant?
Are you on any medications?
Do you consume protein in your meals?
Do you have high body temperatures?
Are you on protein diet?
Have you puked or had diarrhea recently?
Do you eat a lot of food with protein?
Do you have any malnutrition disorders?

Depending on the answers given to the questions and the blood test parameters the proposed machine learning mechanism produces disease estimation and preventive measures to be taken. The proposed machine learning algorithm for disease estimation and preventive measures to be taken for the estimated disease from the blood test parameters is specified below:

Algorithm: Proposed Machine Learning Approach Disease and Preventive Measures Estimation from Blood Test Parameters

1. Load blood test parameters dataset
2. Assume disease_label is the column indicating the presence or absence of a disease
3. Split the data into training and testing sets

4. Standardize the features
5. Train a Machine Learning Classifier
6. Select the feature based on importance
7. Use the selected features for training and testing
8. Train the model with selected features
9. Evaluate the model
10. Estimate the disease using the trained model
11. Provide recommendations for preventive measures based on the estimated risk of the disease.
12. Assess and estimate the appropriate preventive measures based on the likelihood of the disease.

The algorithm outlined above is employed to estimate diseases and recommend preventive measures based on blood test parameters.

III. Implementation Details and Experimental Evaluation of Proposed Machine Learning based Blood Test Parameters Estimator

Recurrent The proposed machine learning approach disease and preventive measures estimation from blood test parameters is developed using Anaconda with Python 3.9 distribution. For the development of the proposed approach sqlite3, tkinter, PIL, ImageTk, and sklearn python libraries are used. SQLite emerges as a sleek database engine crafted in the C language, seamlessly integrating into applications not as a separate entity but as an intrinsic library. This integration positions it within the realm of embedded databases. The creation of the sqlite3 module is attributed to Gerhard Häring, offering an SQL interface that aligns with the DB-API 2.0 standard, necessitating SQLite version 3.7.15 or later for optimal functionality.

SQLite is akin to a nimble library in C, offering a compact disk-based database sans the need for a distinct server process, and it embraces a unique dialect of SQL for database interaction. It's a go-to for applications to house their data internally. Moreover, SQLite serves as a stellar starting point for app prototyping, with the flexibility to upscale the code to more robust databases like PostgreSQL or Oracle. On another front, Tkinter ties Python to the Tk GUI toolkit, standing as the quintessential Python pathway to this interface and claiming the title of Python's default GUI. Python installations across Linux, Windows, and macOS come bundled with Tkinter, ready out-of-the-box.

The ImageTk module is a treasure trove for crafting and tweaking BitmapImage and PhotoImage objects within Tkinter, all originating from PIL's canvas. It's the magic wand that turns any PIL masterpiece into a Tkinter-friendly bitmap image, ready to be slotted into any corner where Tkinter anticipates an image's embrace. These images must don the "1" mode like a badge of honor, with zero-value pixels donning the cloak of invisibility. Any options you whisper to it are like secret messages passed straight to Tkinter's ears. Among these, 'foreground' is the star, setting the stage for the vibrant hues that fill the non-transparent segments. For the curious minds, the Tkinter scrolls hold the secrets to color specification.

The ImageTk module is the artist's ally, offering tools to shape and refine Tkinter BitmapImage and PhotoImage canvases. Parallelly, the Image module stands as a class under the same moniker, embodying a PIL image. This module is a factory of possibilities, churning out functions to summon images from the digital ether or forge new visual creations. In the realm of Python, scikit-learn (once known as scikits.learn and affectionately termed sklearn) is a bastion of free machine learning lore. It's a treasure trove of algorithms for classification, regression, and clustering, boasting the likes of support-vector machines, random forests, gradient boosting, k-means, and DBSCAN. Crafted for harmony, it dances in sync with the numerical and scientific librettos of NumPy and SciPy.

In the proposed research work a database is designed in the sqlite3 for storing the features patient name, patient ID, gender, country, region, Age, WBC, Neut(%), Lymph(%), RBC, HCT(%), Urea, Hb, Creatinine, Iron, HDL, and Alkaline Phosphatase. These stored features are useful to locate the patient data uniquely and to define the blood test parameters of the patient. The dataset, encompassing over 1100 records, is employed to condition the suggested model on variables such as Age, WBC, Neut(%), Lymph(%), RBC, HCT(%), Urea, Hb, Creatinine, Iron, HDL, Alkaline Phosphatase, smoke, pregnant, medications, protein, high temperatures, diarrhea recently, malnutrition disorders, and disease_label. In the proposed model, "disease_label" serves as the outcome variable, and the other 19 parameters function as the input features for the model's training process. The dataset used to train the proposed model comprises in all 20 features.

A graphical user interface is designed to test the proposed model. Upon logging into the designated interface, the user is required to enter their blood test parameters into the subsequent input screen, as depicted in figure 1. User can enter the patient's related parameters namely patient name, patient ID, gender, country, region, Age, WBC,

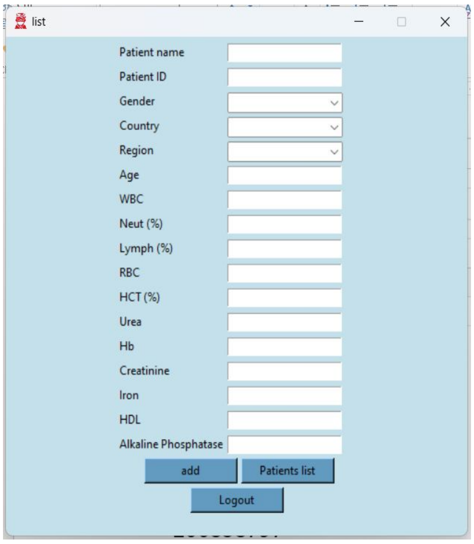

Figure 1: Interface for Providing Blood Test Parameters with Patient Information

Neut(%), Lymph(%), RBC, HCT(%), Urea, Hb, Creatinine, Iron, HDL, and Alkaline Phosphatase in the interface as shown in figure 2. Figure 2 displays the entered blood test parameters for a patient named Vikram, while Figure 3 illustrates the same for a patient named Sunil.

After inserting the blood test parameters in the interface user can click on add button to insert value into the database. After this user can click on the patient list. The patient list after adding patient Vikram is shown in figure 3 and patient list after adding patient Sunil is shown in figure 4.

The user can analyze the specified blood test parameters by inserting the patient id in the field in front of Analysis by Id button as shown in figure 5. Once user click on the Analysis by Id button a questionnaire is displayed to the user. Users can give answers in Yes/ No by asking these questions to the patient as shown in figure 6. Once user clicks on the Analyze button shown in figure 6 user gets the entire disease and preventive measures estimation for the current blood test parameters. The estimated disease and preventive measures for blood test parameters of patient Vikram are shown in figure 7. Figure 8 shows the estimated disease and preventive measures for blood test parameters of patient Sunil.

From figure 7 it can be observed that Vikram has 50% the chances of disruption of blood production, 25% chances of blood disease and 25% chances of liver disease. While Sunil has 33.33% the chances of disruption of blood production, 33.33% chances of infection and 33.33% chances smoking related diseases. The preventive measures suggested for Vikam are 10 mg pill of B12 a day for a month and 5 mg pill of folic acid a day for a month for disruption of blood production, a combination of cyclophosphamide and corticosteroids for blood disease, and referral to a specific diagnosis for the purpose of determining treatment for liver disease. The preventive measures suggested for Sunil are 10 mg pill of B12 a day for a month and 5 mg pill of folic acid a day for a month for disruption of blood production, dedicated antibiotics for infection, and stop smoking for estimated smoking related diseases.

From the overall analysis of the proposed implemented system it is found that the proposed machine learning based estimator estimates the disease and preventive measures more accurately. The overall accuracy of the proposed system is 89.24%.

IV. CONCLUSION

The existing approaches for blood test parameters estimation are presented in this paper. In the proposed research work dataset features and blood test parameters are utilized to estimate the patient condition based on the blood test parameters. The proposed machine learning approach disease and preventive measures estimation from blood test parameters is proposed, designed, developed, and evaluated in this chapter. Age, WBC, Neut(%), Lymph(%), RBC, HCT(%), Urea, Hb, Creatinine, Iron, HDL, Alkaline Phosphatase, smoke, pregnant, medications, protein, high temperatures, diarrhea recently, malnutrition disorders, and disease_label these 20 features are utilized to train the proposed approach. A graphical user interface is designed to evaluate the proposed approach. Anemia, Bleeding, Hyperlipidemia, Disruption of blood production, Hematological disorder,

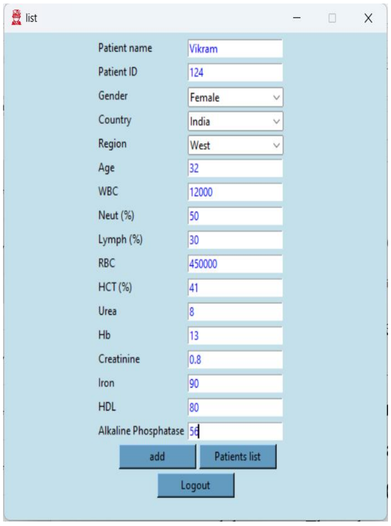

Figure 2: Patient's Blood Test Parameters Entered by User for Patient Vikram

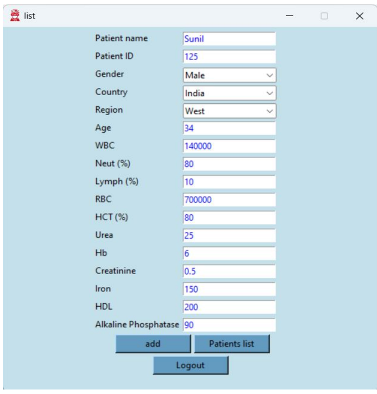

Figure 3: Patient's Blood Test Parameters Entered by User for Patient Sunil

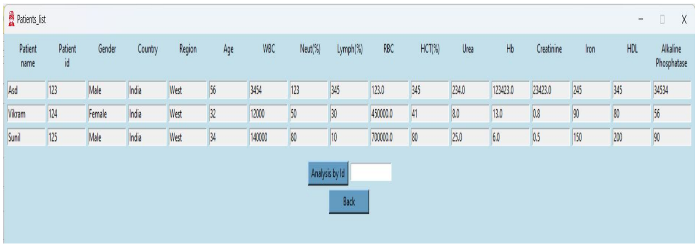

Figure 4: Patient List after Adding Patient Sunil

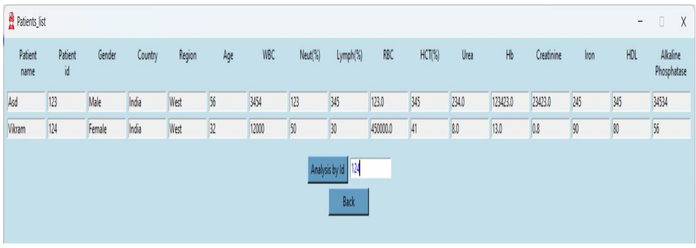

Figure 5: Specifying Patient ID for Blood Test Parameter Analysis

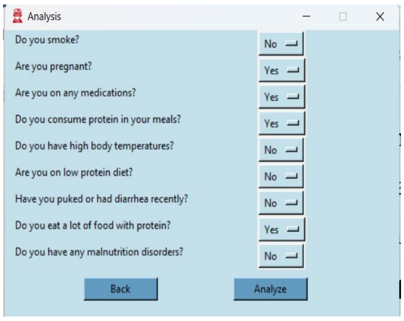

Figure 6: Answers given to Questionnaire

Iron poisoning, Dehydration, Infection, Vitamin deficiency, Viral disease, Diseases of the biliary tract, Heart diseases, Blood disease, Liver disease, Kidney disease, Iron deficiency, Muscle diseases, Lung disease, Overactive thyroid gland, Adult diabetes, Cancer, and Malnutrition these disease can be estimated by the proposed approach along with their preventive measures. The overall accuracy of the proposed system is 89.24%.

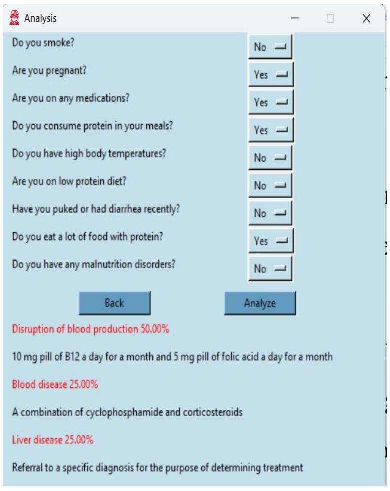

Figure 7: Estimated Disease and Preventive Measures for Vikram

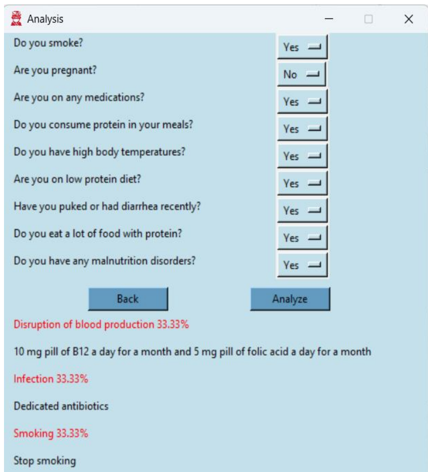

Figure 8: Estimated Disease and Preventive Measures for Sunil

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