**Non-Invasive Level Estimation of Blood Glucose and Haemoglobin Using Neural Network**

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**ABSTRACT**

Diabetes is one of the prominent diseases around the world. Presently, invasive techniques need a finger-prick blood sample. A repetitively painful procedure that produces the chance of infection. A device for blood Hemoglobin measurement was designed and developed without pricking the blood. This non-invasive device is based on the principle of NIR spectroscopy technique with specific short wavelengths for detection of Hemoglobin molecules. The proposed technique is implemented using emitters and cameras of particular specifications and ratings. The data acquisition module is also implemented with combinations of emitters and Camera to collect the data. The proposed non-invasive device is examined by placing fingertips into the embedded clips which contain emitters and detectors. Hence, continuous blood Hemoglobin monitoring is possible through developed prototypes. The mechanism of Hemoglobin detection is that when light of specific wavelengths passes through the object, then received resultant light corresponds to change in blood Hemoglobin concentration. These collected spectrums are interpreted in the form of blood Hemoglobin concentration using a machine learning-based CNN model.

**Keywords:** Non-Invasive Method, Blood Hemoglobin, Near-infrared (NIR) spectroscopy, CNN

1. **INTRODUCTION**

422 million diabetic people have been reported in 2019 according to the WHO database. The people are found in low- and medium-income countries. In 2019, 69.2 million Indians of the population had type 2 diabetes. Approximately 2.35 million adults have Type 1 diabetes. Diabetes takes place when a person faces difficulty in balancing the body Hemoglobin level in different prandial states. Diabetes is caused by the deficiency of insulin with respect to the generated Hemoglobin in the body. It may be due to the demolition of insulin which is produced by beta cells in the pancreas. Diabetes may also be caused by insulin resistance. This is a condition in which the muscles, fat and liver cells of the body do not consume insulin effectively.

Diabetes is classified into three parts: Type 1 diabetes, Type 2 diabetes and gestational diabetes. In type 1 diabetes, the immune system of the body attacks and destroys the cells of the pancreas which produce insulin. This results in the affected person who will be unable to generate insulin naturally. Type 2 diabetes is the most common diabetic stage which is most commonly seen in people over the world. In this type of diabetes, the pancreas will be able to generate some amount of insulin. Gestational diabetes occurs in women in the later stages of pregnancy. Most common symptoms of diabetes are the excretion of urine within short durations, consistently hungriness, thirsty, unexpected weight loss, tiredness and vision changes. The long duration of diabetes without any treatment may cause kidney disease, stroke, heart disease, nerve damages and blindness. After these problems, the probability of death with diabetes has become 50% higher than without diabetes in adults. Diabetes may be controlled through physical exercise, diet, and proper use of insulin regimen. Oral medications are also useful to control for an early stage of diabetes. Controlling of diabetes also includes reduction of risk factors for cardiovascular disease such as lipid profile, high systolic and diastolic blood pressure. In most cases of adults, 5% Type 1 diabetic patients have been considered approximately in all diagnosed cases. Whereas, 90-95% Type 2 diabetic patients have been considered for treatment. Type 1 diabetic patients must have insulin to control the blood Hemoglobin level. Type 2 diabetic patients can control their Hemoglobin level by following an optimized diet with medication and a regular physical exercise schedule. By using a noninvasive device for continuous blood Hemoglobin measurement, the patient can have a proper dose of insulin or other kind medication and can control the blood Hemoglobin level during physical activities. A certain meal is also needed to control diabetes.

1. **METHODOLOGY**

Presently available invasive glucometers and wearable minimally invasive patches are not advisable for frequent monitoring. These would cause trauma due to pricking the skin multiple times. Therefore, non-invasive approaches are reported as precise solutions in terms of continuous Hemoglobin measurement. The available noninvasive devices are also not precise in terms of Hemoglobin measurement of diabetic patients. Some devices are precise but these are limited to the Hemoglobin measurement range (preferred range is 90-150 mg/dl). This is also not advisable for day to day measurement purposes. Hence, it is necessary to develop a device which can measure the blood Hemoglobin non-invasively for all kinds of people (healthy and diabetic).

The goal of this paper is to explore a unique approach to measure blood Hemoglobin without pricking the blood. A device has been designed with the implementation of the proposed technique. The proposed device is a system on PCB along with the data acquisition module. The Camera and components which are used to implement the proposed technique are comparatively low cost and easily available in the market. Because of this, the solution will be cost-effective. The Camera is light weighted and can be worn on the finger and wrist just like a wearable system. The non-invasive system is required to design which should be user friendly and supports continuous Hemoglobin monitoring (CHM). The Medical framework is also required for diagnosis and treatment of remote located diabetic patients. The closed loop system is needed to design which measures the Hemoglobin and provide the insulin dose to control the Hemoglobin of diabetic patients.

**2.1 Related Work**

Many commercial continuous blood Hemoglobin measurement devices use cost-effective electrochemical sensors [11]. They are available to respond quickly for Hemoglobin detection in blood [12]. Lancets (for pricking the blood) is used at the primary stage for blood Hemoglobin monitoring for various commercial devices available in the market [13]. The frequent measurement through the process is so much panic due to picking the blood sample from the fingertip more than 3-4 times in a day for frequent monitoring[14]. A low-invasive amperometric Hemoglobin monitoring biosensor has been proposed using a fine pointed Hemoglobin oxidase immobilized electrode which doesn’t require more than 1mm in length to be inserted in skin [15]. The photometric approach has been explored for Hemoglobin measurement using small blood volumes [16]. The issue of high volume of pricking blood has been solved by this system for testing. A fully implanted first-generation prototype sensor has been presented for long-term monitoring of subcutaneous tissue Hemoglobin [17]. This wearable sensor which is integrated as an implant is based on a membrane containing immobilized Hemoglobin oxidase and catalase coupled to oxygen electrodes, and a telemetry system.

**2.2 Minimally Invasive and Non-invasive Methods**

Implantable sensors have been deployed for continuous Hemoglobin monitoring [18]. Biosensors have been designed for patient use massively and successfully for one time invasive [19]. Wearable minimally invasive microsystems have been explored for Hemoglobin monitoring [20]. A microsystem has been presented for Hemoglobin monitoring which consists of microfabricated biosensor flip-chip bonded to a transponder chip [21]. The output signal has been measured by this transponder chip of the biosensor and transmitted the measured data back to the external reader. A method has been discussed to reduce the frequency of calibration of minimally invasive Dexcom sensors [22]. An artificial pancreas has been represented along with a Hemoglobin sensor to control diabetes [23]. But, approaches based semi-invasive devices have not been tried for real-time application. These wearable microsystems are neither painless nor cost-effective solutions.

Non-invasive approaches of measurement are more advanced compared to the current invasive method to make the painless device [14], [15]. The portable system of measurement (SoM) of the non-invasive Hemoglobin measurement device is desirable for smart healthcare systems [10]. A lot of approaches have been introduced for Hemoglobin measurement [16]. Non-invasive approaches of measurement are more advanced compared to the current invasive method [14], [15]. The optical method is more reliable, cost-efficient for Hemoglobin measurement according to the analysis of researchers [17], [18]. There are varieties of various optical techniques for noninvasive measurement such as photoacoustic spectroscopy [19], polarimetric, near infer-red spectroscopy, Raman spectroscopy and scattering spectroscopy [20]. For the development of a non-invasive measurement device, it is considered by the researcher that the device would be much more convenient for the user’s perspective [21]. In this way, improvement of the accuracy and reliability of these devices have been considered as essential objectives. Calibration and blood to interstitial Hemoglobin dynamics have been considered for the accuracy of continuous Hemoglobin monitoring system [34]. Several calibration algorithms have been developed and implemented for portable setup. Sometimes, accuracy is not considered as a serious issue as per reliability and error detection [16]. But, reliability has been approved for main requirements and tried to improve it [17]. In the further direction, a self-monitoring system is embedded and includes detection of abrupt faults [18]. A lot of work has also been done on fault detection for continuous monitoring.

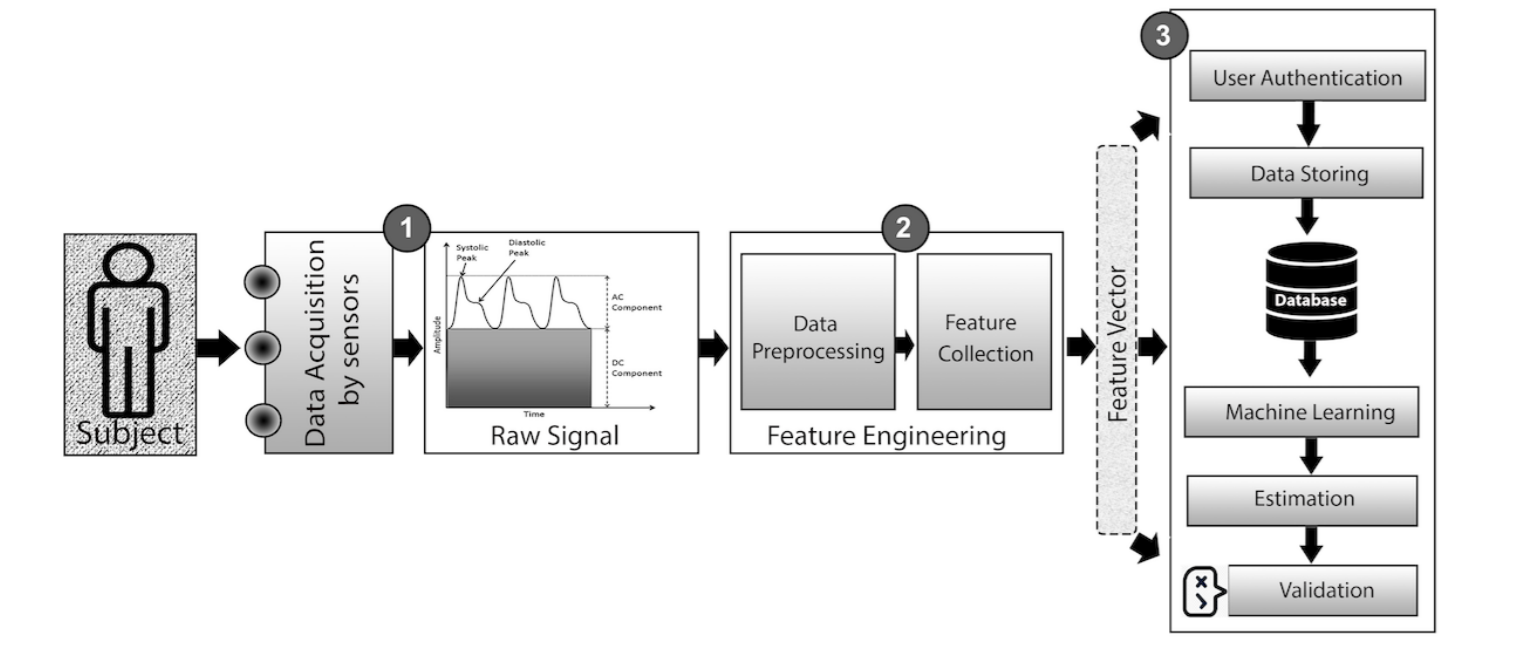
**2.3 Near-Infrared Spectroscopy**

Infrared spectroscopy (IR spectroscopy or Vibrational Spectroscopy) involves the interaction of infrared radiation with matter[40]. It covers a range of techniques[41]. It is based on scattering, absorption and reflection spectroscopy [22]. The absorption of IR waves causes the generation of vibrations of the molecular atom and causes of band spectrum which are usually expressed by wavenumber cm−1 [23]. In this technique, the light in the near-infrared range (700 nm – 2500 nm) is passed through the object (ear lobe or finger) [24]. The passed light through the finger or earlobe interacts with the components of blood and gets reflected, absorbed and scattered [25]. The penetration depth will be varied with a change in wavelength [26]. According to Beer-Lambert law, the attenuation of light in tissue or vessel relates the intensity of light, reflection, scattering coefficient and path length of light through tissue or vessel [27]. Attenuation occurs due to absorption of scattering of light [28]. The value of absorption coefficient depends upon the change in Hemoglobin concentration [29]. The value of Hemoglobin concentration in blood vessel could be indicated due to change in intensity of transferred light through the vessel [30]. The change in Hemoglobin concentration is measured through light detector [31].

1. **PROPOSED METHOD**

# In this project, proposing approaches for blood Hemoglobin level measurement with the aim of recommending data collection techniques, signal extraction processes, feature calculation processes, machine-learning algorithms for developing a noninvasive Hemoglobin level estimation using a smartphone. There is worldwide demand for an affordable Hemoglobin measurement solution, which is a particularly urgent need in developing countries. The smartphone, which is the most penetrated device in both rich and resource-constrained areas, would be a suitable choice to build this solution. This Project proposes a noninvasive Hemoglobin level measurement process. Also it compares the variation in data collection sites, biosignal processing techniques, theoretical foundations, photoplethysmogram (PPG) signal and features extraction process, machine-learning algorithms, and prediction models to calculate Hemoglobin levels. This analysis was then used to recommend realistic approaches to build a smartphone-based point-of-care tool for Hemoglobin measurement in a noninvasive manner A noninvasive (without blood sample collection) approach involves data obtained from image sensors, spectroscopic information, and output of a photoplethysmography (PPG) sensor to calculate the Hb level.

# A smartphone-based POC tool as a potential alternative to invasive clinical blood testing is rapidly attracting attention because of the advantages of availability, user-friendliness, and easy attachability to different biosensing devices. The fingertip area is one of the best data collection sites from the body, followed by the lower eye conjunctival area. Near-infrared (NIR) light-emitting diode (LED) lights were identified as potential light sources to receive a Hemoglobin response from living tissue. PPG signals from fingertip videos, captured under various light sources, can provide critical physiological clues. The features of PPG signals captured under NIR LED are considered to be the best signal combinations following a dual-wavelength theoretical foundation. The PPG signal is generated from each video, and multiple characteristic features are then extracted from the PPG signal, its derivatives and from Frequency analysis. genetic algorithms (GA) have been used to select the optimal features (Feature selection). Finally, CNN based models have been developed to estimate the blood Hemoglobin (Hb) levels from the selected features. The approach expected to provides the best-estimated accuracy of around 98%



**Figure 1:** Architecture Diagram of proposed System

**3.1 NIR Estimation Mechanism**

# We present an optical detection technique of absorbed and reflected light. Absorption and reflectance spectroscopy at 940 nm and absorption spectroscopy at 1300 nm are implemented for detection of the Hemoglobin molecules. The obtained voltage from the detector depends on the received light intensity. After placing the fingertip between emitter and detector, the voltage values are logged. Hemoglobin molecule concentration depends upon the change in light intensity.

# During experimental work, blood Hemoglobin is measured through the invasive device SD check glucometer for validation of the non-invasive results. The reading is taken as referenced blood Hemoglobin concentration (mg/dl). At the same time, optical responses (in mV) through detectors have been collected from three channels simultaneously. During measurement, the channel's data is collected in the form of voltages from three detectors. These collected voltages will be corresponding to referenced blood Hemoglobin concentration. These voltage values are converted into the decimal form using highly precise 4-channel ADS 1115 (from texas instruments) analog to digital converter [124]. The absorbance or scattering (resultant voltage values) is taken as 128 samples per second. The coherent averaging is done after logging the data from the ADS 1115. The coherent averaging has been performed for the calibration of the device. During validation of the data, the averaging is done from 1024 samples which have been logged from ADS in 8 seconds.

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# Figure 2: NIRS based Hemoglobin estimation.

1. **RESULTS AND DISCUSSION**

**4.1 Machine-Learning (ML) Method for Device Calibration**

# CNN models (RM) are calibrated to analyze the optimized computation model for blood Hemoglobin estimation. The detector’s output from three channels is logged as input vectors for prediction of Hemoglobin concentrations.

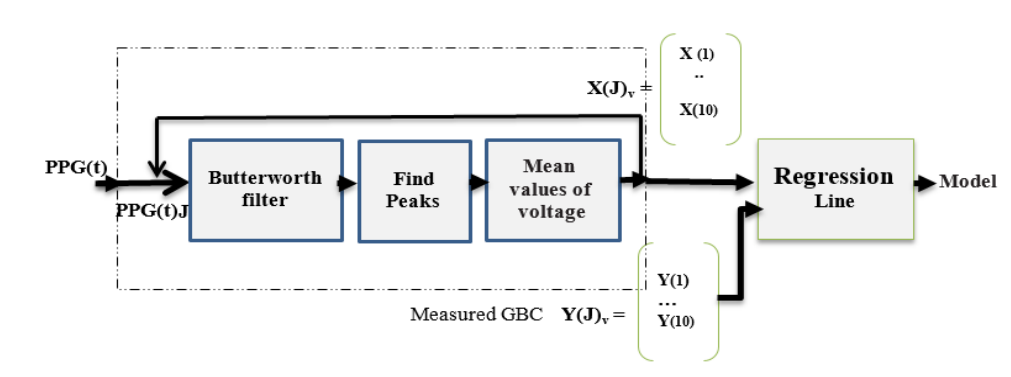
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# Figure 3: Estimation Block Diagram.

# The calibrated models are used to predict the blood Hemoglobin concentrations for validation. The collected data from the samples are required to be converted in the form of estimated blood Hemoglobin concentration values. It is necessary to design an optimized kernel for precise measurement of the predicted Hemoglobin concentration value. 97 samples are taken for device calibration which includes prediabetic, diabetic and healthy samples.

**4.2 PPG Calculation**

There are some properties that vary from person to person which could influence the PPG reading such as the circumference of a subject's finger, the different body fluid concentration, and the roughness of the skin that can cause the scattering of light, etc. In order to avoid this influence and improve the system performance, each person is required to perform ten measurements in order to construct his private individual calibration model, the blood glucose concentration of each person is then predicted based on his private individual calibration model. After smoothing the PPG signal using the Butterworth filter, the calibration model between the PPG data and reference values of BGC was built as shown in Figure 4.



# Figure 4: PPG WorkFlow.

The mean value of voltage is calculated from the peaks of PPG data obtained, as there exists a functional relationship between the PPG signal and blood glucose level [24], the voltage intensity of PPG signal changes with variation in glucose concentration. Ten means voltage is calculated from ten PPG readings for the same subject and put into a vector and put the ten reals GCB readings for the same subject into a vector, then used the two vectors as input data for constructing the regression model.

(1)

(2)

Where  Vector voltages PPG readings.

 : Vector reals GCB readings.

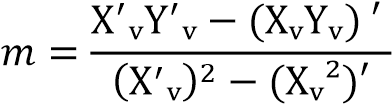
To construct the regression model, the regression line must be calculated. The general linear regression model is given by:

 (3)

Where Y: The predicted blood glucose concentration.

X: The voltage of the PPG signal.

The (m) and (b) are the regression coefficients which is given by:

 (4)

 (5)

Where  the mean of vector voltages PPG readings.

 the mean of the vector reals GCB readings.

1. **CONCLUSION**

We have successfully designed and developed a non-invasive Hemoglobin measurement device for universal healthcare. NIR light with specific wavelengths has been determined and validated using experimental analysis for Hemoglobin molecule detection. A multiple short wave spectroscopy technique is implemented to develop the proposed device. An optimized CNN model is analyzed for precise Hemoglobin estimation. The developed device has been calibrated and validated through healthy, prediabetic and diabetic patients. With the active support of the diabetes center, real-time testing has been done directly through all types of patients. The proposed device has been integrated with a proposed framework for patient monitoring, cloud access by the patient and doctor and storage of Hemoglobin values. The error analysis has been done using Clarke error grid analysis of healthy, prediabetic and diabetic patients individually and combined analysis has also been performed for cross-validation. Experimental analysis has also been performed to analyze the device stability using different objects for measurements. The proposed device has also been compared with previously published approaches based on non-invasive devices in terms of error analysis and limitations of devices. During analysis, it is concluded that the proposed device is more precise for serum Hemoglobin measurement compared to capillary blood Hemoglobin measurement. Hence, a non-invasive Hemoglobin measurement device with the integration of the proposed framework has been introduced for smart healthcare in this work.

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