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Bloodless Haemoglobin level Detection using Deep Convolution Neural Network

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ABSTRACT

The classic "fingerstick" test, which involves invasively extracting blood from the body, is used to quantify haemoglobin (Hb). Although traditional laboratory measurements are reliable, they have their own drawbacks, such as time delays, patient inconvenience, biohazard exposure, and the lack of real-time surveillance in crucial circumstances.Through non-invasive hemoglobin assessment (SpHb) researchers can easily help diagnose polycythemia, anaemia, and a variety of cardiovascular illnesses and that's why it has gotten a lot of attention. Deep Convolutional Neural Network (DCNN) based picture research for haemoglobin level detection is investigated in this work. We used a heterogeneous evaluate accurately with various haemoglobin levels to train. It displays the concentration of haemoglobin in a realistic situation during testing.

Keywords: Deep Learning, CNN, non-invasive, Haemoglobin detection, DCNN

I. INTRODUCTION

Haemoglobin (Hb) is a complex biological molecule production of red blood cells that transports oxygenated blood to the body's organs and tissues while also transporting away carbon dioxide heart to the lungs. A sufficient haemoglobin level must always be maintained to ensure appropriate tissue oxygenation, screen for and help identify diseases that impact Red Leukocytes, and assess the degree and classification of anaemia or polycythemia. The determination of haemoglobin is one of the most routine laboratory examinations. Testing is performed during a systematic health assessment when a person shows signs or symptoms of a disorder that affects red blood cells, such as anaemia or associated characteristics.

when a person is diagnosed with continuous bleeding problems or chronic anaemia, this test may be repeated oftentimes or frequently. patients undergoing cancer therapy are given a haemoglobin test to determine the success of their treatment. one of the required steps in making judgments about blood transfusions is a haemoglobin test. The classic "fingerstick" test, which includes invasively extracting blood from the head, quantifies haemoglobin. After cleaning the finger, the health professional will pierce the tip with a tiny needle (or lancet) to collect the blood. collecting a blood sample is only painful for a brief time and can feel like a short pinprick. even though traditional laboratory measurements are dependable, it has some drawbacks, i.e., time delays, patient annoyance, unsafe exposure, and the shortage of actual surveillance in critical situations.

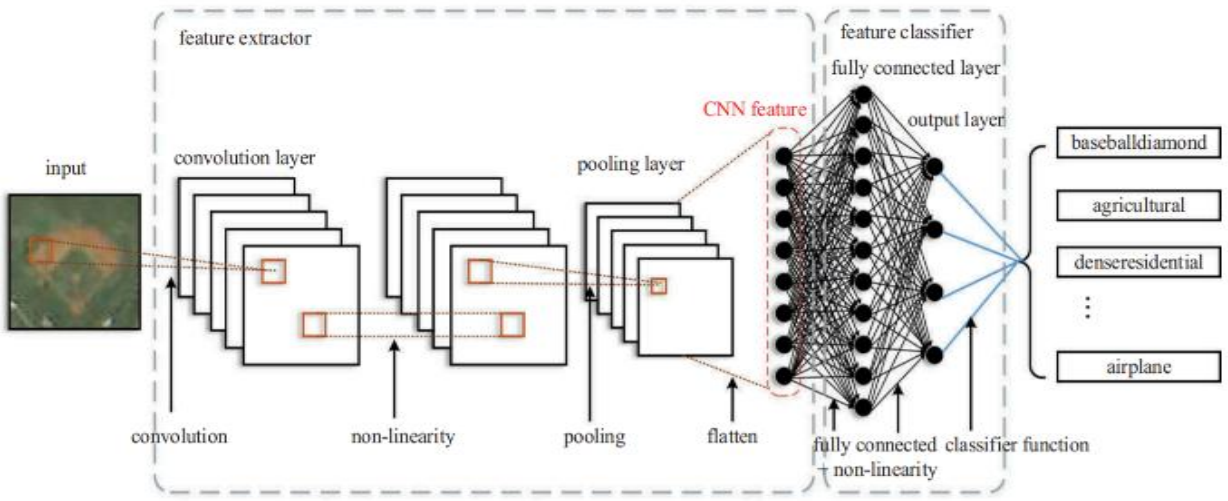

Figure 1 : Framework of Deep CNN using RESNET-100

II. LITERATURE SURVEY

In all vertebrates, haemoglobin (Hb) is a metalloprotein found in red blood cells (RBC) that contains iron and transports oxygen [1]. Hb deficiency has been linked to premature births, low birth weight, and maternal death [2]. According to the WHO (World Health Organization), there is a total of 24.8 % shortage of Hb in the whole world. Hb in the blood can be calculated using a variety of ways. The CBC (Complete Blood Count) is a clinically accepted method of taking uncomfortable, time-consuming, and expensive blood. As a result, it's challenging to diagnose continuously, especially in pregnant women and ICU patients, when a Hb level test is required regularly. Men's blood sugar levels should be between 13.5 and 17.5 gm/dl, while women's blood sugar levels should be between 12 and 15.5 gm/dl. However, less than 10 gm/dl is considered a deficiency of Hb in clinical terms. A total of 104 data points were obtained from individuals for this study. Eighty-one data points are picked from the complete dataset to train the model, while 23 data points are kept aside for further testing the algorithm.

There are 54 males and 50 females of various ages among the 104 data. Chittagong Medical College Hospital in Chittagong and Cox's Bazar Medical College Hospital in Cox's Bazar Medical College Hospital in Cox's Bazar Medical College Hospital in A smartphone camera with a 12-megapixel camera was used to photograph everyone's conjunctiva. The Hb level is also noted and validated by doctors on the CBC (Complete Blood Count) Report, tested in a diagnostic centre. This CBC report was used to determine the fundamental Hb level. Within two or three days of the test, this report was completed. Images of the conjunctiva of the eyes were taken, and image processing was used to extract red, green, and blue percentages. Our goal is to use regression to predict numeric haemoglobin values. Different regression techniques, such as Multivariate Linear Regression (MLR), Linear SVR, and Decision Tree (Medium) Tree, are used to train the model that assesses blood Hb level. The results are compared to determine which method is the most accurate. Unlike existing approaches, Machine Learning Technique can produce good overall accuracy in forecasting blood Hb levels. II. CONNECTED WORK Putut Dewantoro et al. [5] developed a smartphone-based noninvasive Hb measurement approach. The PPG signal, which comes from the patient's finger, controls all of the procedures.

For Hb measurement, the overall processing employed the linear regression approach. The instrument gave them a standard deviation of.254gm/dl and a relative standard deviation of 12%. In 2016 Shahzad Bukhari et al. [6] published a study that used a noninvasive device to assess Hb levels. Hb in blood flow was measured using the spectrophotometric technique. To determine the Hb, the gadget was put in the index finger. Researchers used the invasive lab results as a baseline against which they compared the noninvasive results. They discovered that the accuracy was 92 percent, the sensitivity was 89 percent, and the specificity was 76 percent. Recall Kavasaoglu et al. [7] Hb evaluation based on PPG signal features, where the properties of the PPG signal are used to produce a forecast. CART (classification and regression trees), GLR (generalised linear regression), LSR (least squares regression), MVLR (multivariate linear regression), GRNN (generalized regression neural network), RFS (RELIEF feature selection), and SVR (support vector regression) are few of the machine learning algorithms that are used. PPG signals from 33 persons were acquired for this study, and 40 characteristics were derived from them. Using SVR, they got a mean square error of 0.0027. Soumil Chugh and Jaskirat Kaur presented a method [8] for measuring haemoglobin levels in the blood using the principle of photoplethysmography and the Beer-Lambert law. Twelve participants were tested with known Hb levels, and the results showed a 10% variation from the correct amount.The researchers created a wearable printed circuit board (PCB) that collected reflection-type PPG signals and measured heart rate and oxygen saturation. Sen Gupta et al. [9] built a PPG data gathering device that recorded both transmission- and reflection-type signals and then used a machine-learning algorithm to identify a set of features associated with blood glucose levels from the signs to predict blood glucose concentration. PPG signals can also be used to evaluate other health-related indicators, including glycated haemoglobin (HbA1c). The authors of [10] used digital volume pulse waveforms, often known as fingertip PPG signals, to build grey-box models for estimating HbA1c.

PPG waveforms using various physiological parameters such as heart rate, vascular compliance, blood viscosity, and respiratory frequency in order to estimate blood glucose were analyzed by Monte-Moreno et al. [11]; For blood-glucose level classifications and reclassifications they used a support vector machine (SVM), random forest, linear regression, and a Neural Network Classifier (NNC). When a photon is ejected from a light source, it is either reflected by tissue components and returned to the PD or transmitted through tissue and reaches the PD on the other side of the photon source. The PPG signal identifies changes in blood volume by following the transmission or reflection mode. In our research, we used Monte Carlo (MC) simulation to look at photon propagation through a finger model with blood as a static component and looked at changes in blood volume. MC simulation is a method of computing that uses random sampling of an absolute amount. It is a technique for mimicking photon transmission in biological tissues that is adaptive. The simulation is based on photons doing random walks through tissue, for step size and angular deflection per scattering event determined by sampling the probability distribution (f(x)). Light transport in tissues is modelled using a random walk process that each photon packet passes through within the tissue model [12], a famous MC modelling method.

Before entering the tissue model, an initial weight is assigned to each photon packet delivered. For a unit path length, the absorption coefficient a (cm1) and scattering coefficient s (cm1) are assigned to represent the probability of

absorption and scattering[13]. The probability distribution of the scattering angles for first-order approximation is determined by the anisotropy factor g which is defined as the standard cosine of the scattering angle. Furthermore, the rise of refraction is determined by the change in refractive index n between any two areas in the tissue model or at the air–tissue interface. A portion of the photon packet leaves from the same side of the tissue model after travelling through a specific medium; this fraction is determined as the part of the incident light that is scored as the received light intensity (weight). notably, the transmittance [14] is accomplished via the negligible quantity of the photon packet weight that goes via the medium and leaves on the other aspect of the model. The number of photons that reach the PD was studied to deduce the association between the received light intensity and blood-glucose content in this work, which used MC simulations to infer photon transport within the finger tissue model. Light vehicle in a tissue medium has recently been used to estimate health-related indicators in vivo, such as blood pressure, blood glucose concentration, and blood oxygen saturation [15]. MC simulations are the gold standard for photon migration in the tissue model to measure health parameters [16] noninvasively.

Noninvasive blood-glucose assessment is a new research topic, and the MC approach has only been used in a few studies. Backpropagation MC (BpMC) was introduced by Liu et al. [17] to recover the bio-optical properties of multilayered tissues from transmitted and reflected light signals. Two types of models, BpMC-DEE and BpMC-CNN, were employed to estimate blood glucose concentrations using these features. A near-infrared tunable semiconductor laser and an integrated detector were used in [18] to propose frequency-modulated continuous-wave (FMCW) LIDAR technology for estimating blood-glucose concentrations, and MC simulations were done to examine the method's practicality. By evaluating the relationship between signal strength and light transit time depending on beat frequency, the glucose content was derived from the slope of the FMCW signal spectrum.

Enejder et al. [19] used Raman spectroscopy for quantitative, noninvasive blood-glucose measurements, testing 17 healthy human volunteers and collecting 461 sets of Raman spectra transcutaneous, coupled with glucose reference values. Each participant was also subjected to partial least-squares calibration and leave-one-out cross-validation. The R2 value was 0.83 0.1, according to them. [20] developed fluorescence-based glucose sensors for in vivo blood-glucose estimation using innovative receptor systems for glucose recognition and transduction techniques. The obtained optical signals were used to measure glucose concentrations using a mathematical model in this technique, and the assessments were done on raw optical signals. However, a simple mathematical model cannot account for the logical links between visual data and physiological indicators, making it difficult to apply the proposed strategy in clinical settings.

III. PROBLEM STATEMENT

In this research work to design and develop system for detection of haemoglobin level using collaboration of deep learning techniques.

Objectives

- To study and analysis various non-invasive haemoglobin detection in real time scenario.
- To develop an algorithm for detect the haemoglobin level of users based on finger image.
- To develop an Deep Convolutional Neural Network (DCNN) for detection of haemoglobin in real time scenario.
- To explore and validation the accuracy of proposed system with various existing systems.

Proposed System Design

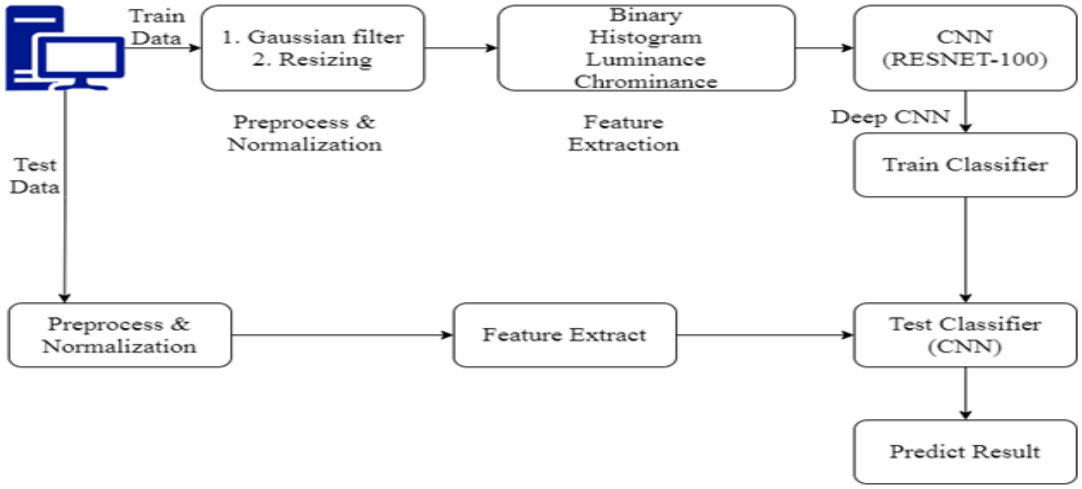

Figure 2 : Proposed system architecture

System Modules

1: Data pre-processing and normalization

2: Feature extraction and selection

3: Module training (DCNN)

4: Module Testing (DCNN)

5: Result haemoglobin level report generation

Algorithm Design

CNN Training

Training Process

Input: Training dataset TrainData [], various activation functions [], Threshold Th

Output: Extracted Features Feature_set[] for completed trained module.

Step 1: Set input block of data d[], activation function, epoch size,

Step 2: Features.pkl ← ExtractFeatures (d[])

Step 3: Feature_set [] ← optimized (Features.pkl)

Step 4: Return Feature_set []

CNN Testing

Input: Training dataset TestDBLits [], Train dataset TrainDBLits [] and Threshold Th.

Output: Resultset <class_name, Similarity_Weight> all set which weight is greater than Th.

Step 1: For each testing records as given below equation, it works in convolutional layer for both training as well as testing

$$\text{testFeature(k)} = \sum_{m=1}^{n} (.\ \text{featureSet[A[i] ... . A[n]} \leftarrow \text{TestDBLits})$$

Step 2 : Create feature vector from testFeature(m) using below function.

Extracted_FeatureSet_x [t…..…n] = $\sum_{x=1}^{n}(t) \leftarrow$ testFeature (k)

Extracted_FeatureSet_x[t] is the outcome of each pooling layer that is extracted from each convolutional layer and forward to net convolutional layer. This layer holds the extracted feature of each instance for testing dataset.

Step 3: For each train instances as using below function,

$$\text{trainFeature(l)} = \sum_{m=1}^{n} (.\ \text{featureSet[A[i] ... . A[n]} \leftarrow \text{TrainDBList})$$

Step 4: Generate new feature vector from trainFeature(m) using below function

Extracted_FeatureSet_Y[t……n] = $\sum_{x=1}^{n}(t) \leftarrow$ TrainFeature (l)

Extracted_FeatureSet_Y[t] Is the outcome of each pooling layer that is extracted from each convolutional layer and forward to net convolutional layer. This layer holds the extracted feature of each instance for training dataset.

Step 5: Now evaluate each test records with entire training dataset, in dense layer

$$\text{weight} = \text{calcSim (FeatureSetx} \,||\, \sum_{i=1}^{n} \text{FeatureSety[y]})$$

Step 6: Return Weight

Outcome of system:

- It will show the level or count of haemoglobin of specific user using DCNN.

RESULTS AND DISCUSSIONS

Intel i7 CPU 2.7 GHz has used with 16 GB Random Access Memory for execution. The RESENT (32,50, 101 and 152) version has used for experimental investigation of proposed systems including 5G network. The major factors has considered execution time (including data processing, data uploading and downloading etc.), memory consumption, network overhead and energy for valuation the efficiency of proposed systems.

Table 1 : Data processing time with various deep models

Data Samples	CaffeNet	Google Net	Alex Net	VGG Net	RESNET
100	73.2	73.5	74.2	73.98	79.23
200	76.2	77.2	75.7	74.2	81.6
500	75.2	79.5	77.8	76.6	82.3
1000	77.1	78.9	76.2	77.0	83.2

The above Table 1 describes an data processing time for all deep models using TensorFlow for different data size.

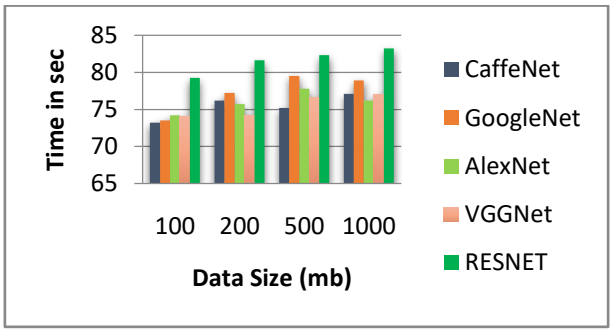

Figure 2: Accuracy of system with deep models

The above Figure 2 also describes a visual interpretation of Table 1 that provides how accuracy should be increased when data load has enlarged. It sometimes depends on current trained modules and heterogeneous data module.

REFERENCES

[1]. Maton, Anthea, Jean Hopkins, Charles William, Mclaughlin, Susan Johnson, Maryanna Quon Warner, David LaHart, Jill D. Wright (1993). Human Biology and Health. Englewood Cliffs, New Jersey, USA: Princeton Hall. ISBN 0-13-981176-1

[2]. Monika Malhotra, “Severe Anemia linked to poor outcomes for pregnant women and their babies”, International Journal Gynecology and obstetrics, vol. 79 p p93-100, 2002

[3]. World Health Organization “Nutritional Anemias. Report of a WHO scientific group,” World Heal Organ—Tech Rep Ser, 405:5-37, 1968.

[4]. Prevalence of Anemia, “Department of Nutrition for Health and Development, World Health Organization,” Geneva, Switzerland. WHO Vitamin and Mineral Nutrition Information System, Public Health Nutr. April 2009.World Health Organization. Worldwide prevalence of anemia. WHO Rep. 51, 2005.

[5]. Putut Dewantoro, Clinton Elian Gandana, Resti Oktia Rahman Hasballah Zakaria, Yoke Saadia Irawan, “Development of Smartphonebased Non-Invasive Hb Measurement”.

[6]. Shahzaib Bukhari et al. "Transforming Community-based Screening of Total Hb using Non-invasive Devise," IEEE Conference on Technologies for Sustainability (SusTech),2016

[7]. A. Resit Kavasaoglu, Kemal Polat, M. Hariharan, “Non-invasive prediction of Hb level using machine learning techniques with PPG signal’s characteristics features,” Elsevier Science Publishers B. V. Amsterdam, vol. 37, Issue C, pp. 983-991, December 2015

[8]. Soumil Chugh, Jaskirat Kaur, “Non-Invasive Hb Monitoring Device,” 2015 International Conference on Control, Communication & Computing India (ICCC) | 19-21 November 2015 ,Trivandrum

[9]. Sen Gupta, S.; Kwon, T.-H.; Hossain, S.; Kim, K.-D. Towards Non-Invasive Blood Glucose Measurement Using Machine Learning: An All-Purpose PPG System Design. Biomed. Signal Process. Control 2021, 68, 102706.

[10]. Hossain, S.; Gupta, S.S.; Kwon, T.-H.; Kim, K.-D. Derivation and Validation of Gray-Box Models to Estimate Noninvasive in-Vivo Percentage Glycated Hemoglobin Using Digital Volume Pulse Waveform. Sci. Rep. 2021,
[11]. 12169. [CrossRef] 11. Monte-Moreno, E. Non-Invasive Estimate of Blood Glucose and Blood Pressure from a Photoplethysmograph by Means of Machine Learning Techniques. Artif. Intell. Med. 2011, 53, 127–138.
[12]. Jacques, S.L.; Wang, L. Monte Carlo Modeling of Light Transport in Tissues. In Optical-Thermal Response of Laser-Irradiated Tissue; Lasers, Photonics, and Electro-Optics; Welch, A.J., van Gemert, M.J.C., Eds.; Springer: Boston, MA, USA, 1995; pp. 73–100, ISBN 978-1-4757-6092-7.
[13]. Wisotzky, E.L.; Uecker, F.C.; Dommerich, S.; Hilsmann, A.; Eisert, P.; Arens, P. Determination of Optical Properties of Human Tissues Obtained from Parotidectomy in the Spectral Range of 250 to 800 Nm. J. Biomed. Opt. 2019, 24, 1–7.
[14]. Zhu, C.; Liu, Q. Review of Monte Carlo Modeling of Light Transport in Tissues. J. Biomed. Opt. 2013, 18, 050902.
[15]. Nawaz Jadoon, R.; Shahzad, A.; Shah, S.A.A.; Khan, M.A.; Akram, T.; Zhou, W. Veins Depth Estimation Using Diffused Reflectance Parameter. Appl. Sci. 2020, 10, 8238.
[16]. Periyasamy, V.; Pramanik, M. Advances in Monte Carlo Simulation for Light Propagation in Tissue. IEEE Rev. Biomed. Eng. 2017, 10, 122–135.
[17]. Liu, W.; Huang, A.; Wang, P. BpMC: A Novel Algorithm Retrieving Multilayered Tissue Bio-Optical Properties for Non-Invasive Blood Glucose Measurement. In Proceedings of the 2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Kansas City, MO, USA, 13–16 November 2017; pp. 451–456.
[18]. Xiong, B.; Wei, W.; Liu, N.; He, J.-J. Monte Carlo Simulation of Non-Invasive Glucose Measurement Based on FMCW LIDAR. In Proceedings of the Optics in Health Care and Biomedical Optics IV, Beijing, China, 18–20 October 2010; International Society for Optics and Photonics: Bellingham, WA, USA, 2010; Volume 7845, p. 784518.
[19]. Enejder, A.M.K.; Scecina, T.G.; Oh, J.; Hunter, M.; Shih, W.; Sasic, S.; Horowitz, G.L.; Feld, M.S. Raman Spectroscopy for Noninvasive Glucose Measurements. J. Biomed. Opt. 2005, 10, 031114.
[20]. Moschou, E.A.; Sharma, B.V.; Deo, S.K.; Daunert, S. Fluorescence Glucose Detection: Advances Toward the Ideal In Vivo Biosensor. J. Fluoresc. 2004, 14, 535–547.