Real-time and Non-Invasive Detection of Haemoglobin level using CNN

Suresh Mestry[1], Kasturi Shinde[2], Dhanita Redij[3], Rajeshwari Tajnekar[4]

[1] Assistant Professor, Dept. of Computer Engineering, MCT'S Rajiv Gandhi Institute of Technology, Maharashtra, India

[2,3,4]Student, Dept. of Computer Engineering, MCT'S Rajiv Gandhi Institute of Technology, Maharashtra, India

---

Abstract – *The traditional technique of haemoglobin detection involves extraction of blood from the body. Even if these laboratory measurements are reliable, they have their own drawbacks, such as time delays, patient inconvenience, biohazard exposure, and the lack of real-time monitoring in critical situations. Bloodless haemoglobin measurement has gotten a lot of attention from researchers since it can help diagnose polycythemia, anemia, and other cardiovascular disorders earlier. In this study, image analysis using a Convolutional Neural Network is used to detect haemoglobin levels. We used a heterogeneous image dataset with various haemoglobin levels to train the model . We have designed a web application that displays the level of haemoglobin in a real-time scenario during testing.*

Keywords: ***Non-Invasive, Deep Learning, CNN, Haemoglobin level detection, real time***

1. INTRODUCTION

Haemoglobin (Hb) is a composite molecule of red blood cells, within the lungs, within the lungs of oxygen, and returns the CO2 back to the lungs within the tissue. to make sure appropriate tissue oxygenation on the screen and to assess the severity and diagnosis of red blood cells you want to maintain a sufficient level of haemoglobin to assist you diagnose the acceptable conditions for red blood cells. Haemoglobin measurement is one among the foremost frequently performed laboratory tests. This test is performed when health care is usually tested or when an individual has signs and symptoms of the countries that folks affect red blood cells like anemia or polynomials. This test also will be held several times or regularly when someone is diagnosed with current bleeding issues or chronic anemia.

When a person is willing to donate blood the first thing that the doctors check is the haemoglobin level. The classic "fingerstick" test is performed to extract the blood from the body that helps to determine haemoglobin. Firstly, the finger is cleaned and then the health professionals will prick the tip with the lancet to collect the blood. Collection of blood samples are often temporarily uncomfortable and faster. Traditional laboratory measurements are accurate, but have limitations like delay, patient discomfort, exposure to biohazards, and lack of real-time monitoring in critical situations.

2. Literature Survey

Haemoglobin[HB] is a metalloprotein found in red blood cells that contains iron and carries oxygen[1] There is a growing interest in assessing anaemia using ocular pallor in NEA investigations. Researching non-invasive approaches to assess anaemia requires significant effort in order to support clinical innovations and procedures that decrease personal pain and enable widespread screening. The main goals of this study are to analyse the area of interest explored in the NEA literature, to evaluate the peculiarities of papers, with a special focus on empirical ones, and to examine them from the perspective of daily improvement of doctors' and healthcare personnel's activities, as well as the daily lives of patients; and to identify any significant research gaps in order to encourage further research on new topics. Methodology: Because it specifies a rigorous methodology for data retrieval and interpretation, the systematic mapping research has been chosen as the best method for probing the NEA literature. Findings: This field of research is quite busy, especially in the world's most populous nations, and it focuses on enhancing existing technology and offering new solutions, particularly portable and useable by everyone[2].

The procedure its haemoglobin is measured at the tip of any finger, using a light source consisting of an infrared LED and a red LED, and a photodiode detecting the absorbed light. The empirical equation for calculating haemoglobin concentration in blood is obtained using a model for light attenuation through skin, tissue, and blood in that extremity, as well as well-known haemoglobin extinction factors (with and without oxygen). Software technologies such as signal processing and filtering are used to further analyse the received signal. The results of the measurements are provided, along with a viable answer, and the research has to be refined further[3].

In utilizes specific aspects of PPG data and multiple machine literacy ways to develop anon-invasive approach for prognosticating haemoglobin. PPG signals from 33 persons were included in 10 ages in this study, and 40 distinct characteristics were recaptured. In addition to these characteristics, each subject's gender(manly or womanish), height(in cm), weight(in kg), and age were all taken into account. The" Hemocue Hb201TM" instrument was used to test the blood count and haemoglobin position at the same time. colorful machine learning retrogression ways(bracket and retrogression trees – wain, least places retrogression –

LSR, generalised direct retrogression – GLR, multivariate direct retrogression – MVLR, partial least places retrogression – PLSR, generalised retrogression neural network – GRNN, MLP – multilayer perceptron, and support vector retrogression – SVR) were used. The stylish features were chosen using RELIEFF point selection(RFS) and correlation- grounded point selection(CFS). The multiple machine learning algorithms were utilised to estimate the haemoglobin position using original data and chosen characteristics utilising RFS(10 features) and CFS(11 features)(4).

Anon-invasive device that monitors the volume of Glycosylated Haemoglobin(HbA1c) utilising detectors and machine literacy algorithms A breath analyzer with detectors is included inside the contrivance to measure how important moisture, temperature, and acetone a person has gobbled. The supervised machine literacy system Artificial Neural Network(ANN) will be utilised to assay and link the observed acetone position to HbA1c position. Temperature, moisture, detector voltage, and detector resistance are all mainly connected with glycosylated haemoglobin position, according to the results of the neural network retrogression. The HbA1c position anticipated will be divided into three(5) groups. Hyperparameter optimization utilising the support vector machine(SVM) fashion was used to categorise the three groups of HbA1c values.(6)

The traditional ways of blood group identification include skin puncturing, infections, conking , are time- consuming, and need the use of reagents. The suggested system is small in size, affordable in cost, takes lower time, and produces results instantly. When compared to traditional approaches, the blood group is detected in a fairly short period. There's no need to perforation the skin; we can determine the blood type without doing so. In the event of an exigency, hospitals will be suitable to determine the blood group in a short period of time.(7)

Before entering the towel model, an original weight is assigned to each photon packet delivered. For a unit path length, the immersion measure a(cm1) and scattering measure s(cm1) are assigned to represent the probability of immersion and scattering(8). 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. likewise, the rise of refraction is determined by the change in refractive indicator n between any two areas in the towel model or at the air- towel interface. A portion of the photon packet leaves from the same side of the towel model after travelling through a specific medium; this bit is determined as the part of the incident light that's scored as the entered light intensity(weight). specially, the transmittance(9) is fulfilled via the negligible volume 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 conclude the association between the entered light intensity and blood- glucose content in this work, which used MC simulations to infer photon transport within the cutlet towel model. Light vehicle in a towel medium has lately been used to estimate health-affiliated pointers in vivo, similar as blood pressure, blood glucose attention, and blood oxygen achromatism(10). MC simulations are the gold standard for photon migration in the towel model to measure health parameters(11) noninvasively.

3. PROBLEM STATEMENT

The classic" fingerstick" test, which involves invasively removing blood from the body, is used to quantify haemoglobin(Hb). Although traditional laboratory measures are dependable,they have their own downsides, such as time holdbacks, patient vexation, biohazard exposure, it will also be proved convenient for blood donation camps and the lack of real- time surveillance in pivotal circumstances. In this design we design and apply system for discovery of haemoglobin position using collaboration of deep literacy ways.

ideal

• To study and analysis non-invasive haemoglobin discovery in real time script.

• To develop an algorithm for descry the haemoglobin position of druggies grounded on cutlet image.

• To develop an Deep Convolutional Neural Network(DCNN) for discovery of haemoglobin in real time script.

• To explore and confirmation the delicacy of proposed system with current systems.

4. PROPOSED SYSTEM

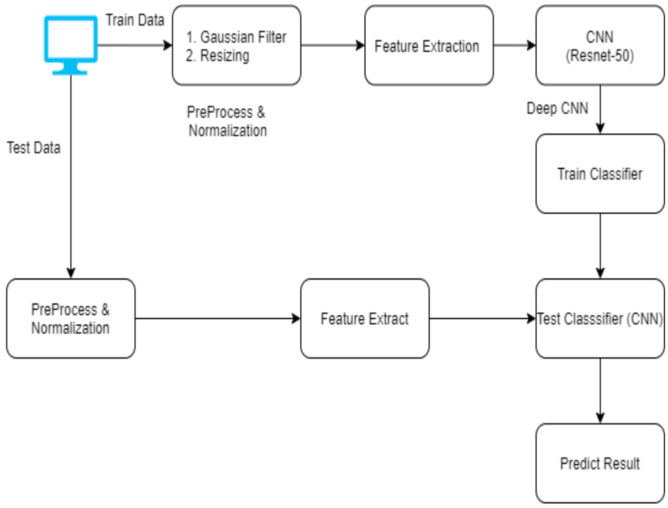

Figure 1: Proposed system architecture

4.1 Data preprocessing and normalization

During pre-processing, distortion correction improves photographs, making future processing easier. Pre-processing processes include colour space conversion, cropping, smoothing, and enhancement. Depending on the image quality, this module's utility varies. According to the literature, colour space conversion is followed by filtration and augmentation. Cropping is also required if images are taken in an uncontrolled environment with intricate backdrops. It can be done either manually or automatically using functions.

4.2 Feature extraction and selection

Feature extraction and selection To comprehend visuals, colour, texture, and shape features are frequently utilised. Color is often determined using moments and histograms. Contrast, homogeneity, variance, and entropy are all features of texture. Shape is also defined by characteristics such as roundness, area, eccentricity, and concavity. A range of features are required for heterogeneous datasets, however texture has been identified as the best feature for plant disease identification. A variety of strategies are used to extract features.

4.3 Module Testing and Training

Module training (DCNN) and Module Testing (DCNN) Classification is an important component of haemoglobin level detecting systems. Because the method employs an image to assess haemoglobin levels, classification refers to the process of categorising finger image data based on the levels that have been recognised. The classifier is trained using photos from a training set, which then classifies or detects images from the test set. To determine haemoglobin levels in a number of ethnicities, researchers used a variety of deep learning algorithms. A low-level haemoglobin image and a high-level haemoglobin image will be distinguished by the classifier.

4.4 Report Generation

In haemoglobin level report generation we demonstrate the accuracy of proposed system and evaluate with other existing system

5. DATASET

We have collected the dataset by connecting to various blood donation camps, creating google forms. We have taken the images of the people who have done the haemoglobin test recently

6. ALGORITHM

In this study we've used the CNN algorithm. It's a special type of neutral network. The convolutional Neural Network CNN works by getting an image, designating it some weightage prognosticated on the different objects of the image, and also distinguishing them from each other. One of the main capabilities of CNN is that it applies primitive styles for training its classifiers, which makes it good enough to learn the characteristics of the target object.

CNN is prognosticated on analogous armature, as set up in the neurons of the mortal brain, specifically the Visual Cortex. Each of the neurons gives a response to a certain stimulant in a specific region of the visual area linked as the open field. These collections stage in order to contain the whole visual area. This algorithm correspond of 3 important part and those are training part and testing part. Training is generally done by combining 3 types of layers those are convolution subset, pooling subset and thick subset. Main point of convolution position is point birth. It's responsible for extraction of various features. Polling caste are applied to down- test the input. The thing is to reduce the computational complexity of the model and to avoid overfitting. There are substantially two different types of Pooling which are as follows Max Pooling The Max Pooling principally provides the maximum value within the covered image by the Kernel. Average Pooling The Average Pooling provides and returns the average value within the covered image by the Kernel. Thick position is responsible to connect every neuron from the former subcaste to the coming bone.

The ideal of these layers is to reduce the dimensionality of the image that's set up in the original input image and to increase dimensionality or, in some cases, to leave it unchanged, depending on the required affair. The same padding is applied to convolute the image to different confines of the matrix, while valid padding is applied when there's no need to change the dimension of the matrix.

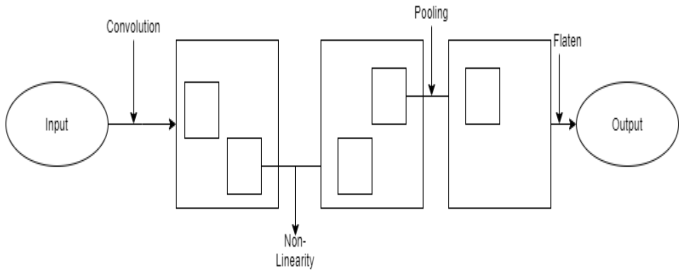

Figure 2: Layers in CNN Algorithm

6.1 CNN Training

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[]

6.2 CNN Testing

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

Expected result: Resultset< class_ name, Similarity_ Weight> all set which weight is more than Th.

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

$$testFeature(k) = \sum_{m=1}^{n} (featureSet[A[i] \ldots\ldots A[n]\ TestDBLit$$

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

$$Extracted\_FeatureSet\_x\ [t \ldots\ldots n] = \sum_{x=1}^{n} (t)\ testFeature\ (k)$$

Extracted_FeatureSet_x[t] is the outgrowth of each pooling subcaste that's uprooted from each convolutional subcaste and forward to net convolutional subcaste. This subcaste holds the uprooted point of each case for testing dataset.

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

$$trainFeature(l) = \sum_{m=1}^{n} (featureSet[A[i] \ldots A[n]TrainDBL$$

Step 4: induce new point vector from trainFeature(m) using below function

$$Extracted\_FeatureSet\_Y[t \ldots\ldots n] = \sum_{x=1}^{n} (t)$$

TrainFeature(l)

Extracted_FeatureSet_Y[t]is the outgrowth of each pooling subcaste that's uprooted from each convolutional subcaste and forward to net convolutional subcaste. This subcaste holds the uprooted point of each case for training dataset.

Step 5: Now estimate each test records with entire training dataset, in thick subcaste

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

Step 6: Return Weight

7. RESULTS AND DISCUSSION

The RESTNET has been used for implementation of the proposed system. The major factors considered here are execution time, memory consumption, network overhead and energy for evaluating the efficiency of proposed system. Intel 17 CPU 2.7 GHz has used with 16 GB Random Access Memory for execution.

Table-1: Accuracy obtained using various deep learning models

Data Samples	CaffeNet	Google Net	AlexNet	VGGNet	RESTNET
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 deep models using TensorFlow for different data size.

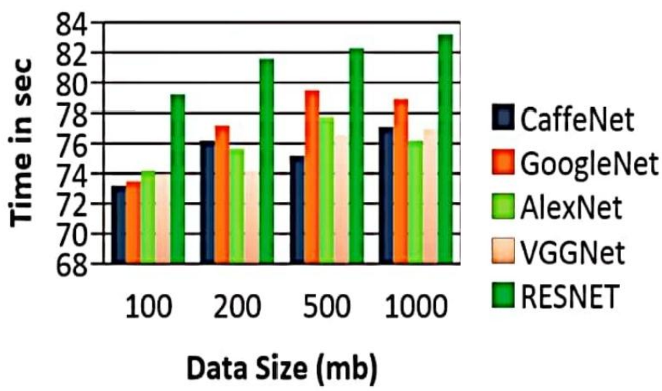

Figure 3: Graphical Representation of accuracy using deep models

The above Figure is a graphical representation of Table 1 that provides how delicacy will be increased when data cargo has enlarged. It occasionally depends on current trained modules and miscellaneous data module.

8. SCREENSHOTS OF THE PROJECT

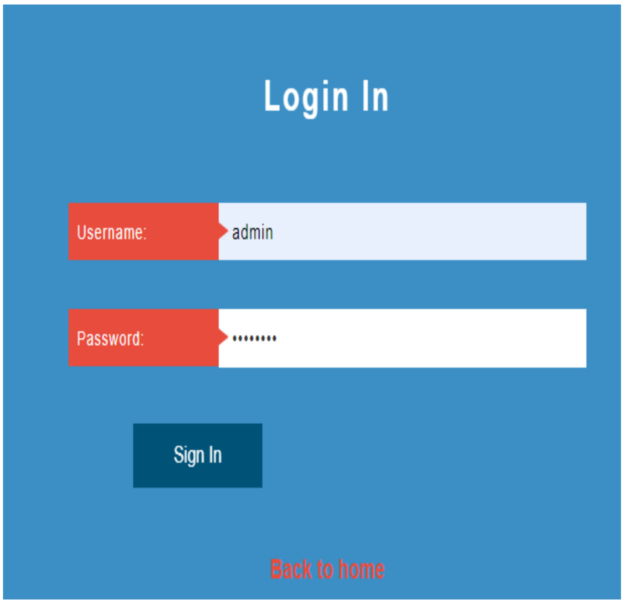

Figure 4: Login page for admin

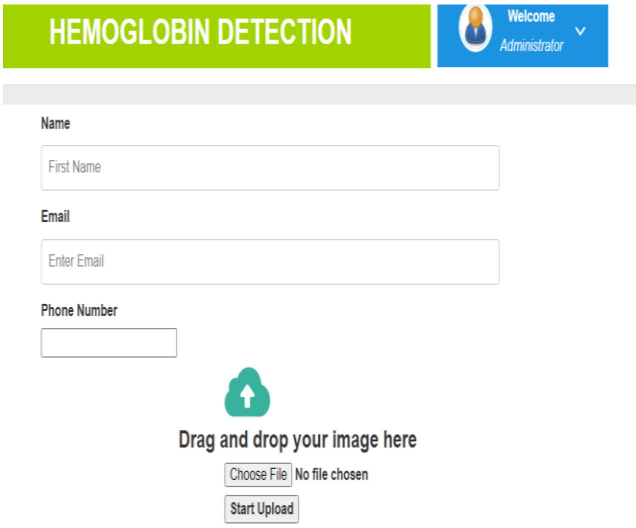

Figure 5: Asking for input details

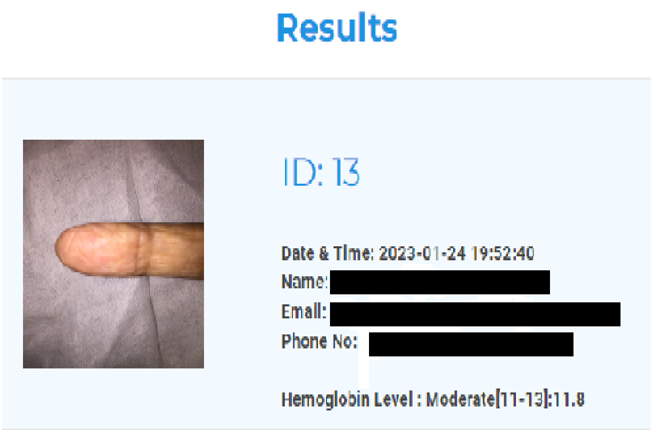

Figure 6: Final result of finger image as input

9. CONCLUSION

Our work focuses on how non-invasive fashion detects the haemoglobin from real- time input images. In medical exploration a problem is set up while trying to break a classifier model due to lack of data for some classes. The imbalance of circumstances may impact the vaticination model. As a result we've cooked an applicable system to break it using a variety of approach.

10. REFERENCES

[1] 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.

[2] 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, AJ, van Gemert, M.J.C., Eds.; Springer: Boston, MA, USA, 1995;

[3] Wisotzky, EL: Uecker, FC, 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.

[4] 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.

[5] Lui W; Huang Ai 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

[6] 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.

[7] Moschou, EA.; Sharma, B.V.; Deo, S.K.; Daunert, S. Fluorescence Glucose Detection: Advances Toward the Ideal In Vivo Biosensor J. Fluoresc. 2004, 14, 535-547.

[8] 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

[9] 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

[10] 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.

[11] 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 Haemoglobin Using Digital Volume Pulse Waveform. Sci. Rep. 2021,

[12] Nawaz Jadoon, R.; Shahzad, A; Shah, S.A.A.: Khan, M.A.; Altram, T; Zhou, W. Veins Depth Estimation Using Diffused Reflectance Parameter Appl. Sci. 2020, 10, 8238

[13] Periyasamy, V; Pramanik, M. Advances in Monte Carlo Simulation for Light Propagation in Tissue IEEE Rev. Biomed. Eng, 2017, 10, 122-135

[14] 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

[15] World Health Organization "Nutritional Anemias Report of a WHO scientific group, World Heal Organ-Tech Rep Ser, 405-5-37, 1968

[16] 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,

[17] Putut Dewantoro, Clinton Elian Gandana, Resti Oltia Rahman Hashallah Zakaria, Yoke Saadia Irawan "Development of Smartphonebased Non-Invasive Hb Measurement"