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# Designing a Non-Invasive Anemia Detection System for Sustainable Healthcare

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## ABSTRACT

Technology is revolutionizing healthcare by improving non-invasive medical techniques for diagnosing diseases, as disease images are crucial for numerous medical diagnoses. One of the common illnesses that affects people's health worldwide, particularly children and women of childbearing age, is anemia. By using cutting-edge technology to handle this problem, the prevalence will be significantly lower. A disorder known as anemia occurs when the blood's hemoglobin content falls below normal. In this work, we created a system to find people who are anemic using Mobile Net's deep learning models, versions 2, 3 small, and 3 large. These models were trained and tested on created a dataset of 10,636 color palm images of adults that were labeled as either anemic or not anemic. The high training was Mobile Net v2 accuracy 99.9%, while v3s 81%, v3L 73.7%, and the best test results were in Mobile Net v2 (accuracy 95.77%, precision 96.05%, recall 95.51%, f1-score 95.78%). We have created models to evaluate medical images, automate estimations, reduce diagnosis time and error, and lower fatality rates. They support the sustainable development objectives, especially SDG 3, by encouraging early intervention for better patient quality of life.

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## 1. Introduction

Anemia is a global public health concern that has major effects on people's health [1]. It occurs when a person's hemoglobin (Hb) concentration and/or red blood cell (RBC) counts are below normal and insufficient to meet their physiological needs. It impacts approximately one third of the global population [2]. According to the World Health Organization, 40% of pregnant women and 42% of children under the age of 59 months are anemic overall [3][4]. This affects about 33% of the world's population. [5]. The pandemic affects about 1.62 billion people, with prevalence rates five times higher in low-income countries and inversely correlated with economic status [6]. In these low-income societies, iron deficiency anemia is thought to cause about half of all cases of anemia. Other causes, like malnutrition, micronutrient deficiencies, parasitic infections, other chronic inflammatory conditions, or hereditary hemoglobinopathies, also happen a lot.

[6]. Anemia can be categorized into macrocytic, normocytic, or microcytic and severity based on vitamin B12, inflammation, or iron deficiency. However, traditional methods for diagnosing anemia pose significant challenges for underprivileged groups, as they often lack access to high-quality healthcare services and high laboratory testing costs [7]. Usually, the first test performed for the diagnosis is the complete blood count (CBC) test, which contains elements such as red blood cells (RBCs), white blood cells (WBCs), hemoglobin, hematocrit, and platelets [8]. The majority of conventional anemia screening methods measure hemoglobin (Hb) levels using invasive blood tests, which are the gold standard but can be challenging to administer, especially in settings with low resources [9]. Diagnosing anemia involves taking blood samples from patients, testing results in a lab, using advanced surgical tools, and requiring expensive procedures. Frequent blood collection can cause discomfort and risk blood-borne infections, affecting patients and medical professionals [10]. Subjective pallor assessments on the tongue, palms, nail beds, and conjunctiva of the eye are noninvasive ways to find severe anemia. So are deep learning-based methods that use electrocardiograms or smartphone apps to look at the color of your fingernails. However, these methods are limited by variability in sensitivity, specificity, and reliability, especially in diverse populations and uncontrolled environments [11]. Noninvasive techniques, such as blood sample collection, have gained popularity as an alternative to invasive methods due to their minimal risk of infection, real-time patient monitoring, and portability [12]. Artificial intelligence, including machine learning and deep

learning, is increasingly being applied in scientific domains like health due to its exceptional ability to identify faces and images [13]. Mobile Net is a deep learning network designed for mobile applications, offering a small model size and high computational efficiency. Its features include customizable design, depth-wise separable convolution, and scaling multipliers for flexibility in adjusting model size based on application needs [14]. This study presents a system using deep learning models and mobile networks to reduce the impact on public health, enhance early detection, and support the Sustainable Development Goals. Goal 3 of the United Nations Sustainable Development Goals prioritizes health and well-being for all ages, which aligns with effective anemia by

- Enhancing Health Outcomes: Deep learning-based early identification can result in prompt treatment, lowering the morbidity and mortality linked to anemia.
- Communities might experience more economic stability and growth as health improves.
- Expanding Access to Healthcare: Deep learning algorithms can enhance screening capabilities in environments with limited resources, expanding access to healthcare for marginalized people [15].

## 2. Literature Review

In recent years, research has primarily concentrated on developing non-invasive methods for identifying anemia through deep learning and artificial intelligence techniques, utilizing images of the palm, conjunctiva, and other relevant locations. In 2015 A. Resit Kavsoglu et al. produced a noninvasive technique to use PPG signal properties to determine hemoglobin. Photoplethysmography, which measures variations in blood volume in the micro vascular bed of tissues, was performed on 33 people with 10 periods and 40 characteristics (male or female). Various machine learning algorithms were employed, with support vector regression (SVR) yielding the best results, with the lowest mean square error (MSE) value of 0.0027 [16]. In 2016 Shaun Collings et al developed a non-invasive technique to measure conjunctiva pallor using digital photos from a camera or smartphone in order to identify anemia. To determine their erythema index (EI), 106 individuals in the study were given 188 photographs that were analyzed using image software. With a sensitivity of 93% and specificity of 78%, the palpebral conjunctiva erythema index showed the best results when used to identify anemia [17].

In 2017 Yi-Ming Chen et al. suggested noninvasive techniques for identifying anemia in palpebral conjunctiva photos. The technique uses a dataset of

100 adult case palpebral conjunctiva photographs of fixed size, 40 anemic and 60 nonanemic. It combines a Kalman filter with a nonlinear penalty regression algorithm. The findings demonstrate that, for every method taken into consideration, the modified KF considerably lowers the number of questionable samples [18]. In 2018 Monalisha Saikia Borah et al. Utilizing data from 1500 patients, a variety of machine learning algorithms were employed to detect betathalassemia and HbE. The best results were obtained with decision tree and random forest algorithms, which achieved average precision, recall, and F1-scores of 93.89%, 92.78%, and 93.33%, respectively [19]. In 2019 Manish Jaiswal et al. Three classification algorithms Naive Bayes, Random Forest, and Decision Tree—have been implemented in Python using a dataset of 200 CBC test samples. The dataset contains attributes like age, gender, and mean corpuscular volume. Supervisory machine learning uses the algorithms to predict anemia based on CBC data. The Naive Bayes algorithm performs better than the other classifiers, obtaining an accuracy of 96.09% and a mean absolute error of 0.0333 [20].

In 2020 Mangaras Yanu Florestiyanto et al. developed a noninvasive technique for detecting anemia by examining digital images of the nails and palms. The technique involved taking pictures of the nails and palms of 20 participants, 9 anemic and 11 nonanemic, using a smartphone camera in a daylight setting away from direct sunlight. A 90% classification accuracy for anemia was attained using the Naive Bayes classifier [21]. In 2021 Tuba Karagül Yıldız et al. give a study uses Artificial Neural Networks, SVM, Naive Bayes, and Ensemble Decision Trees to classify 12 anemia types using 1663 samples. Bagged Decision Trees achieves the highest accuracy (85.6%). In 2022 Aixian Zhang et al. A deep learning approach using facial image analysis predicts anemia using a convolutional neural network, outperforming two senior physicians' evaluations and achieving an accuracy of 84.02% in predicting anemia from 316 facial videos [23]. In 2023 Shekhar Mahmud et al. suggested a non-invasive technique for identifying anemia utilizing photographs of the lip mucosa by transfer learning with Convolutional Neural Networks (CNN). A camera captured the dataset of 1,380 lip images of men and women, which included 690 normal and 690 anemic samples. For classification, four pre-trained CNN architectures, VGG16, ResNet50, MobileNetV2, and Xception, which got high accuracy (99.28%), and MobileNetV2 (96.38%) [24].

In 2024 Stephen Afrifa et al. suggested a machine learning model for identifying iron deficiency anemia in children. They used six algorithms. The dataset included 4260 palm image observations of both anemic and non-anemic children. The decision tree DT algorithm achieved a high accuracy of 99.92% [25]. In 2025 Rehana Khan

et al. proposed a study for hemoglobin estimation and noninvasive anemia detection using retinal pictures. utilizing a deep convolutional neural network (CNN) with the deep learning algorithms VGG16, ResNet50, and InceptionV3 architectures. High results were obtained at InceptionV3 with 98% accuracy, 99% sensitivity, 97% specificity, and AUC = 0.98 using a dataset of retinal pictures for 2265 subjects aged 40+ who were categorized as anemic and nonanemic. A Scalable Approach for Environments with Limited Resources [26].

### **3. Mobile Net**

Mobile, Net, a deep neural network developed by Google for limited resource devices like smartphones, offers powerful computer vision performance in image classification, object detection, segmentation, and face recognition [27].

#### **3.1 Mobile net versions**

##### **3.1.1 MobileNetV1**

In 2017, the initial version presented the idea of depth-wise separable convolutions. We introduced depth-wise separable convolutions, which reduced the number of calculations by nearly 8–9 times when compared to ordinary convolutions. Use ReLU6 as an activation function. Includes a width multiplier ( $\alpha$ ) to change the speed and size of the model. Includes a Resolution Multiplier ( $\rho$ ) to regulate the size of the supplied image. Mobile gadgets are lightweight, quick, and effective. These devices are crucial for realtime applications. Deeper models are more difficult to optimize because there are no shortcut links [27].

##### **3.1.2 MobileNetV2**

2018 saw the creation of Inverted Residual Blocks, which improved model performance and computational economy. Inverted Residual Blocks, which extend feature maps before depth-wise convolution, are one of the main improvements over V1. After convolution, use linear bottlenecks to minimize feature size. To enhance gradient flow, shortcut connections such as ResNet were added. The expansion layers specifically use ReLU6. ReLU6 provides more accurate object detection and classification compared to V1. Feature representation is superior to that of MobileNetV1. It is more effective in tasks that involve segmentation and object detection. A little more expensive to compute than MobileNetV1 [28].

##### **3.1.3 MobileNetV3**

2019 saw the optimization of MobileNetV2 with strategies such as Neural Architecture Search (NAS) to enhance its precision and effectiveness.

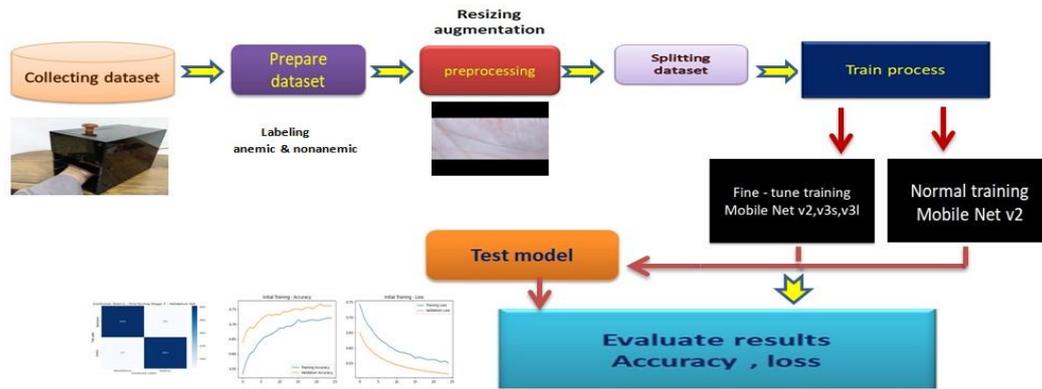


Fig. 1. Methodology block diagram.

One of the main improvements over V2 is the optimization of layer configurations through Neural Architecture Search (NAS). Introduce Squeeze-and-Excitation (SE) blocks to help the model focus on key elements. The model employs Hard-Swish activation instead of ReLU6, thereby enhancing its efficiency. It adopts a hybrid approach by integrating new optimized layers with MobileNetV2 blocks. There are two versions available:

Low-power device optimization is the focus of MobileNetV3-Small. MobileNetV3-Large: Performance optimized. The system is significantly more precise and efficient than MobileNetV2, boasting a more intricate design compared to V1 and V2. Optimal accuracy and speed ratio. SE blocks enhance the learning of features [28].

### 3.2 Normal training

Normal Training (Scratch Training): Randomly initialized weights are used to train the model. The model requires a substantial dataset to achieve effective generalization. Every layer is updated while being trained. It requires additional processing power and time. Helpful in situations where a pre-trained model is unavailable for the task [27].

### 3.3 Fine-tuning training

Fine-tuning training This method makes use of a Mobile Net model that has already been trained on a sizable dataset (such as Image Net). The Mobile Net architecture, a lightweight convolutional neural network, is used in transfer learning to extract features from images, excluding fully connected layers.



Fig. 2. (a) nonanemic image, (b) anemic image.

The pre-trained layers in the Mobile Net model are frozen to prevent alteration during training, ensuring that custom classifier layers are trained using task specific data [29]. Better feature extraction and extremely precise classification are achieved by gradually opening the layers for training while still using the weights from the first training.

## 4. Methodology

The proposed system uses a created dataset, which is collected by a special device designed to collect the data, test, and in the future be connected to a Raspberry Pi with a display. The dataset was labeled into two classes: anemic and nonanemic (3200x1200x3) JPG images, used preprocessing to the dataset, resizing the images to (640x640), and augmented it by rotating the images +5°, -5° and then adding Gaussian blur to the images +20 to increase the dataset, split into percentages of 80% training, 10% validation, and 10% test. Train the dataset with three types of Mobile Net (V2, V3s, and V3l) by using an initial training of 25 epochs with 100 epochs fine-tuned, train the dataset and Mobile Net V2 normal training, and then test all models to give the results. We illustrate the methodology in Error! Reference source not found. below.



Fig. 3. Black box device.



Fig. 4. Shelf with RIO.



Fig. 5. Fields of view of the camera.

#### 4.1 Dataset

The dataset was gathered from Mosul General Hospital and Ibn Sina Teaching Hospital, which are connected to the Nineveh Health Directorate, Ministry of Health for Iraq, following formal institutional clearances and patient consent based on ethical considerations. After the laboratory test was confirmed by measuring blood hemoglobin. The palm patients' images were taken using the Logitech 4K Brio camera at FHD resolution in a comfortable environment at room temperature and with fixed lighting at 70 LUX. The levels vary based on age and gender, but we set the threshold at less than 120 g/L. The collection comprises 2659 palm images of male and female adults aged 18 and over.

We split these images into two classes: 1336 anemic and 1323 non-anemic. We augmented the original images to 10636 in the dataset and tagged them for both groups in order to construct divergences. These divergences enhance dataset diversity, model robustness, and generality. Fig. 2

#### 4.2 Preprocessing

The dataset was classified into two classes: anemic and nonanemic. It was resized from (3200x1200) to (640x640) using letterbox padding to keep the aspect ratio technique and augmented by rotating it to +5° and -5° and adding a Gaussian blur of +20 to increase the dataset from 2659 to 10636 images. Also, split the dataset into 80% train, 10% validation, and 10% test. All preprocessing was implemented by a program in MATLAB 2022a.

displays samples of datasets for the anemic and non-anemic classes.

#### 4.3 Collecting dataset

The dataset was collected using a device that has a special design as a box that has dimensions (25 cm x 15 cm x 20 cm) [30] made from acrylic, a low-weight plastic material with a glossy black color exterior and interior a matte black color as shown in Fig. 3, containing a Logitech 4K Brio camera that provides three options for field of view: 90°, 78°, and 65° with 8 LEDs of type SMD for 1 Watt, 3 volts connected to the rechargeable battery with a potentiometer to choose the optimal illumination for the device. The region of interest (ROI) was placed on a shelf 4 cm from the camera inside the box, with an opening that is 6.5 cm x 8.5 cm and matched the camera aperture at a 90° field of view. To keep the distance between the hand and the camera constant, the hand is positioned beneath it, and then the image is taken as shown in Fig. 4, Fig. 5 and Fig. 6.

#### 4.4 Train process

The dataset has been trained on 3 versions of the Mobile Net network: Mobile Net V2, V3 Small, and V3 Large, implemented by Python in Google Colab and Python 3.12.7 in the Visual Studio Code app. Using an initial training of 25 epochs and 100 epochs of fine-tuning training for four stages, each stage 25 epochs, also trained the datasets with Mobile Net V2 with a normal training of 125 epochs.

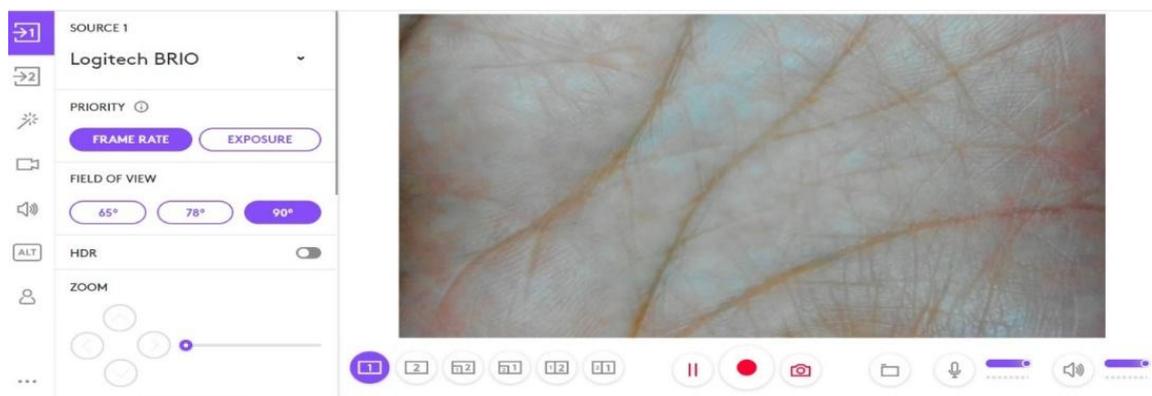


Fig. 6. Image taken by camera.

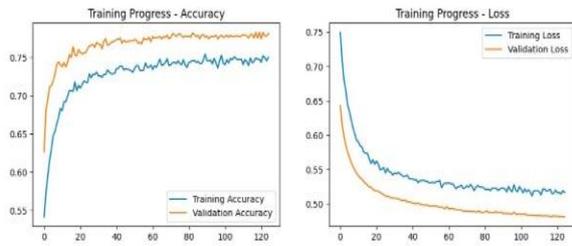


Fig. 7. training accuracy and Loss for V2 normal training at 125 epochs.

#### 4.5 Test and evaluate the models

After finishing the training for each model, test it with the test dataset. The models were given curves of accuracy and loss for training and validation with a confusion matrix for each model at training, validation, and testing, as well as the precision, recall, and F-score for each model.

### 5. Results and Discussion

PC carried out the work according to the specifications. Processor: Intel(R) Core (TM) i7-

In normal training, the learning rate is 0.0001. The model starts at an accuracy of 53% with a training loss of 0.77, a validation accuracy of 62%, and a validation loss of 0.64 at the end. The training has been done with a training accuracy of 85%, a training loss of 0.51, a validation accuracy of 78%, and a validation loss of 0.48. Here the model starts at random weights with low values but gets good values at the end of training because the validation loss is higher than the training loss, meaning that the model is not going to overfitting. Therefore, to improve the results, the model requires an increase in epochs, a larger number of datasets, or a modification in the learning rate. The results are shown below in Fig. 7.

#### 5.1 Fine-tuning training for Mobile Net V2, V3s, V3l

In Fine tuning training all models input image for training 320 with Batch size 32 with 125 epochs,

Table 1. Initial training of Fine-tuning results for all models.

model	precision		recall		f1-score	
	anemic	nonanemic	anemic	nonanemic	anemic	nonanemic
Mobile Net v2	0.49	0.49	0.53	0.45	0.51	0.47
Mobile Nev3s	0.50	0.52	0.78	0.24	0.61	0.33
Mobile Net v3l	0.50	0.50	0.55	0.44	0.52	0.47

4600 M CPU operating at 2.90 GHz and 2.89 GHz with 8.00 GB of installed RAM (7.61 GB usable). System type: x64-based processor, 64-bit operating system. Version 22H2 of Windows 10 Pro Edition. The Visual Studio Code application used Python 3.12.7 to construct models for training and testing using a created dataset. Using input images of 640 pixels in size and Mobile Net versions 2, 3, small, and 3 large for fine-tuning training and regular training, all models were run for 125 epochs.

#### 5.2 Results of training for Mobile Net V2, V3s, V3l

The dataset was split into 80% train, 10% validation, and 10% test, with 8509 images for train, 1063 images for validation, and 1064 images for test. Load the TensorFlow library for training, the Matplotlib and Seaborn libraries for analysis results, and plot curves. All models require 320 input images for training, with a batch size of 32 and 125 epochs.

#### 5.3 Normal training for Mobile Net V2

the fine tuning includes the first part 25 epochs of initial training that start with random weight and trains to learn at first learning rate of 0.0001 made freezing layers during training the results of initial training shown below in Table 1.

Depending on the results of initial training, the Model Mobile v2 and V3 appear to have balanced activities for both classes, but are not accurate, while the Model Mobile v3 is the worst because it is unbalanced for the two classes. The second part of fine-tuning training is 100 epochs divided into 4 sections to unfreeze the layers and open them gradually, each section 25 epochs, reducing the learning rate to 0.00001 with early stopping to control and prevent overfitting using ReduceLROnPlateau: Tracks validation loss and lowers learning rate if model performance stalls for each section. The results of the final section are in Table 2, illustrated below.

Table 2. Fine-tuning results for all models.

model	Train accuracy	Train loss	Validation accuracy	Validation loss
Mobile Net v2	99.9 %	0.00071	95.1 %	0.17
Mobile Net v3s	81 %	0.42	79.3 %	0.43
Mobile Net v3l	73.7 %	0.53	69.9 %	0.69

Depending on the results above the Mobile Net v2 have higher training accuracy 99.9 % with validation accuracy 95.1 % meaning that the model like ideal training but the higher difference between training loss 0.00071 and validation loss 0.17 the model may be in overfitting case but because using early stooping the model did not goes to overfitting, while Mobile Net v3 s has balance activity because that training accuracy and loss near from validation accuracy and loss but the model need more epochs or need more preprocessing to increase the features for learning to increase the accuracy, Mobile Net v3 l low training accuracy 73.7 % meaning that model weak learning because the complexity of the model therefore this model not prefer for this dataset.

### 5.4 Test for Mobile Net V2, V3s, V3l

The model have been tested with two classes, anemic and nonanemic, for 1064 images. The results appear to depend on the confusion matrix in Fig. 8, Fig. 9, and Fig. 10.

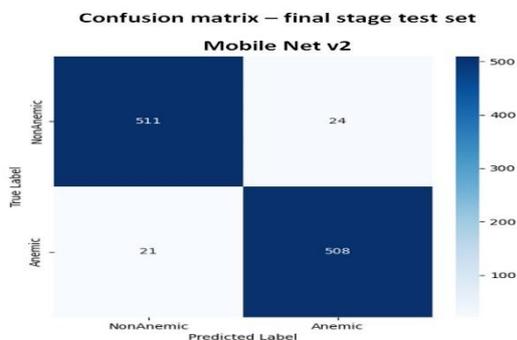


Fig. 8. Test confusion matrix mobile net v2.

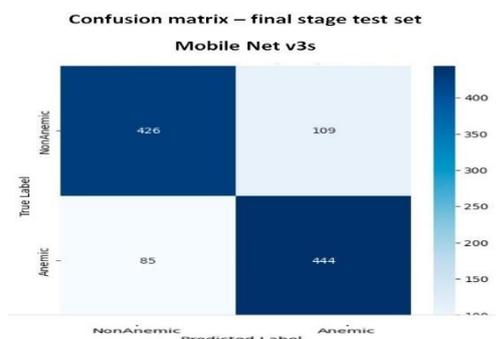


Fig. 9. Test confusion matrix mobile net v3s.

Depended on the test confusion matrix for the models. The results shown in Table 3 are illustrated and results show that the model:

Mobile Net v2: The system performed exceptionally well, achieving a high F1 score of 95.78 percent and accuracy of 95.77 percent. Low FNR (4.49%), indicating that the majority of anemic cases are successfully detected by the model. Low FPR (3.97%), which shows that non-anemic cases were correctly classified. Out of the three models, this one performs the best.

Mobile Net v3s: F1-score (81.45%) and accuracy (81.77%) show moderate performance. High FNR (20.37%) indicates that some cases of anemia are being overlooked. Given the comparatively high FPR (16.07%), the model occasionally incorrectly diagnoses non-anemic individuals. Not perfect, but respectable.

Mobile Net v3l: The accuracy rate was extremely low at 49.62% and the F1-score performance was extremely low at 56.84%. The model frequently incorrectly identifies non-anemic subjects as anemic due to its extremely high FPR (66.92%).

The model, Mobile Net v3 models (both small and large) is not dependable because Overfitting and model complexity may be the cause of poorer performance as compared to v2. Poor generalization may result from the higher model sizes with smaller datasets. Furthermore, for the v3 models to function at their best, more data or im-proved hyper parameter tweaking may be needed. due to We prefer the Mobile Net v2 as the preferred model since it offers the best classification performance and accuracy. Because of the Excellent and consistent performance in training, validation, and testing. The model does not suffer from overfitting because the test accuracy (95.77%) and validation accuracy (95.1%) differ by a comparatively small amount. The best of the three models is the one with the highest accuracy and F1 score.

**Table 3.** result of test for Fine-tuning s of all models.

model	Accuracy	precision	Recall	F1-score	FNR False negative rate	FPR False positive rate
<b>Mobile Net v2</b>	95.77 %	96.05%	95.51%	95.78%	4.49%	3.97%
<b>Mobile Net v3s</b>	81.77%	83.37%	79.63%	81.45%	20.37%	16.07%
<b>Mobile Net v3l</b>	49.62%	49.93%	65.98%	56.84%	34.02%	66.92%

## 6. Conclusion

In this work, a noninvasive system successfully detected anemia by using one of the rapid deep learning models, Mobile Net, with the following versions: 2, 3 S, and 3 L. When using JPG palm images that have been created at Mosul Hospital and Ibn Sina Teaching Hospital, which are connected to the Nineveh Health Directorate, Ministry of Health for Iraq, classified as anemic and nonanemic, the model deals with a splitting percentage of 80% training, 10% validation, and 10% test. The best model that has high training (99.9%) and test accuracy (95.7%) was Mobile Net v2. Because the system is based on a specially designed device for collecting and testing palm images, it can be used to create an anemia detection device after connecting to a Raspberry Pi and demonstrating the potential for future software and hardware tool development. Additionally, the Mobile Net v2 deep learning model can be used to produce a strong noninvasive model to detect anemia with high accuracy of prediction, a very short testing time, and a low-cost using software on a personal PC. Additionally, this technology can increase economic productivity, advance social justice, improve health outcomes, and strengthen early intervention. Furthermore, it can ensure healthy lives and overall well-being, support public health campaigns, and contribute to the achievement of the Sustainable Development Goals.

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