

## RESEARCH ARTICLE

# Blood Oxygen Saturation Measurement: A Survey



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**Abstract:** Although advanced technologies are available to handle complex health issues, the outbreak of COVID-19 is still affecting humans around the globe mentally and physically. To prevent such an outbreak, one approach is to measure oxygen saturation to predict severity early. Therefore, several methods have been developed for predicting accurate oxygen saturation measurements. Due to the non-availability of benchmark and standard approaches, diversified methods have been developed. This leads to confusion about the results, statements, and conclusions. In addition, it hampers the invention of new approaches to address the challenges of oxygen saturation measurement. This motivated us to study different methods of oxygen saturation measurement in this work. The work aims to analyze diverse methods for identifying the strengths and weaknesses of models so that appropriate models can be chosen for specific situations and cases. Furthermore, researchers can have a clear understanding of the state of the art to develop new approaches to address open challenges. The work provides a comprehensive review of different models, their strengths and weaknesses, and a discussion of new challenges, applications, and directions. This can be used as a reference, benchmark, or model for further investigation. To the best of our knowledge, this is the first survey on blood oxygen saturation measurement.

**Keywords:** COVID-19 outbreak, oxygen saturation, predicting models, contact-based models, noncontact-based models

## 1. Introduction

During COVID-19, one of the key factors in monitoring its effects is measuring blood oxygen saturation [1, 2]. Therefore, several methods based on signal processing, image processing, machine learning, and related techniques have been developed to estimate heart rate (HR) from blood oxygen measurements. The reason is that signal processing models are widely used to solve complex problems. Motivated by the surveys and reviews, which remove confusion about state-of-the-art methods in terms of performance, accuracy, scope, and limitations [3], we present a survey on different methods for blood oxygen saturation measurement to discuss merits, demerits, limitations, scope, future challenges, directions, and applications such that readers can determine their objectives without any ambiguity [4].

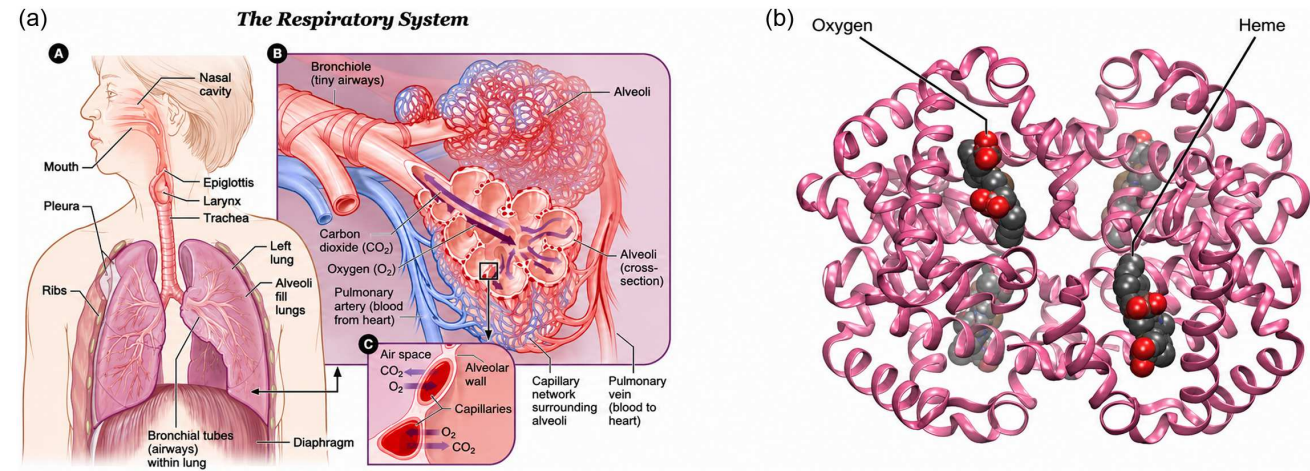
The primary function of oxygen in our body is to provide energy. Approximately 90% of biochemical and metabolic activities are dependent on oxygen [5]. It is noted that atmospheric air contains 21% oxygen. The process of human breathing can be seen in Figure 1(a) [6], where one can understand the mechanism of breathing. During breathing, oxygen travels directly to

the pulmonary alveoli, which are lined with blood capillaries. This enables oxygen to pass from the alveoli into the bloodstream, which bathes all the cells in our body. These cells use oxygen to convert nutrients from digestion into energy that can be used directly by the cells. When oxygen is present, a single molecule of glucose can provide 36 units of energy (ATP), but in the absence of oxygen, it provides only 2 units. Hence, enough concentration of oxygen in our blood is vital for proper metabolism and energy generation.

In the human body, oxygen is mainly carried by red blood corpuscles, which are commonly known as RBCs. Each RBC contains a protein molecule named hemoglobin, as shown in Figure 1(b) [7]. Hemoglobin molecules contain two alpha subunits and two beta subunits; all of them can contain one oxygen molecule. Hence, each hemoglobin molecule is capable of containing four oxygen molecules [7]. When all four units contain four molecules of oxygen, then the oxygen saturation becomes maximum, and the color of blood becomes bright red [7]. But when not every unit contains an oxygen molecule, then the density of oxygen in our bloodstream decreases, and the color of blood remains red, but slightly on the darker side [7]. This is considered under oxygenation. Under-oxygenation of the body is known as hypoxemia. When oxygen saturation is low, the normal functions of the

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Figure 1  
(a) Process of human breathing, (b) molecular structure of hemoglobin



human body halt. Therefore, the lower oxygen saturation causes major issues such as the acute situation of pneumonia, which is one of the major causes of death in kids under 5 years old. Not only kids but also pregnant women and adults over 65 are more vulnerable than the average person. Hypoxemia can occur in people with chronic obstructive pulmonary disease, pulmonary fibrosis, cystic fibrosis, sleep apnea, etc. Hence, many medical procedures require accurate oxygen saturation measurements to function properly.

In recent times, the novel coronavirus (2019-nCoV/SARS-CoV-2) has caused respiratory symptoms, including a substantial pulmonary dysfunction with worsening arterial hypoxemia (low blood oxygenation), eventually leading to acute respiratory distress syndrome. A COVID-19 infection could disrupt one or more of the other major homeostatic pathways. Understanding the nature of crosstalk among normal homeostatic pathways, oxygen-carrying and oxygen-sensing (i.e., hypoxia-inducible factor) proteins, and the mitochondrial respiratory machinery may provide targets for therapeutic interventions [8]. It has been observed that many COVID-positive patients have a low oxygen level even when they feel well [9]. The normal oxygen saturation of a healthy human being is 95–100%. In a recent study on several COVID-19 patients (three patients) ranging in age from 58 to 74 years, SpO<sub>2</sub> was reported to be between 68 and 76%, which is way lower than the range. This might indicate a need for early medical care, as low oxygen levels can be detrimental. Similarly, several applications are shown in Table 1. Although HR

and blood pressure estimation [10, 11] are considered for various health monitoring systems and medical applications, oxygen saturation may provide more vital information, helping medical practitioners take more accurate actions.

Hence, continuous monitoring of oxygen is of great importance. SaO<sub>2</sub> is the measure of arterial oxygen saturation. SaO<sub>2</sub> at the peripheral capillary is called SpO<sub>2</sub>, which is the primary focus of this survey. Unlike traditional SaO<sub>2</sub> measurement, which is normally conducted invasively via a blood test with a blood gas analyzer, SpO<sub>2</sub> can be measured noninvasively. Monitoring SpO<sub>2</sub> provides a quick and convenient assessment of the user's oxygenation status. The most widely used device for SpO<sub>2</sub> monitoring is a pulse oximeter, which is often attached to the finger, earlobe, nose, or other parts of the body for measurement, as shown in Figure 2. But to leverage its contact-based limitations, various attempts have been made, and as a result, it is now possible to measure blood oxygen levels without contact. In this way, one can expect several methods and approaches to measure oxygen levels. This leads the reader to become confused about the benchmark data, results, and challenges. However, the literature indicates that none of the methods discusses standard approaches, evaluation metrics, datasets, or the evaluation process. This creates a void between challenges and invention.

To reduce the gap between challenges and inventions, we present a critical survey that provides a clear idea of the state-of-the-art methods, their strengths and weaknesses, and the remaining challenges.

Table 1  
Applications of blood oxygen saturation measurement

| Areas                  | Application of blood oxygen measurement                                                                                                                           |
|------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Cardiac                | Cardiopulmonary bypass may create a shortfall of O <sub>2</sub> known as “tissue shock.” To avoid this, O <sub>2</sub> saturation measurement is extremely useful |
| Anesthesia             | During anesthesia, post-anesthesia care, including both general and conscious sedation, O <sub>2</sub> saturation is monitored                                    |
| Pulmonary, respiratory | The oximeter is used to monitor respiratory rate and check pulmonary function                                                                                     |
| Metabolism             | A healthy O <sub>2</sub> range indicates good metabolism                                                                                                          |
| Energy                 | Low oxygen saturation indicates a lower number of ATP generation                                                                                                  |
| Covid -19              | A COVID patient has a significantly low O <sub>2</sub> level; measuring O <sub>2</sub> levels in COVID patients is vital                                          |

Figure 2

(a) Device for measuring oxygen level: pulse oximeter; (b) measuring blood oxygen saturation using pulse oximeter



The contribution of this work is as follows. (i) Categorizing the different approaches based on the idea that has been used for developing methods. (ii) Analyzing the strengths and weaknesses of the models technically (qualitatively and quantitatively) according to the situation. (iii) Based on strengths and weaknesses, new challenges, applications, and directions are explored. (iv) To the best of our knowledge, this is the first work, and it can be used as a model and reference for future studies on oxygen measurement.

## 2. Motivation

There are several methods for measuring blood oxygen saturation, namely, contact-based and noncontact-based methods. Contact-based methods rely on the difference in absorption at two specific wavelengths, primarily red and infrared (IR). In this method, the emitted light signal gets captured after it is transmitted/reflected. The difference in the absorption coefficients of tissue, arterial blood, and venous blood at these two wavelengths is used to measure it. On the other hand, noncontact methods mainly use a camera to capture signals as video.

It has been observed that there are conflicts in selecting wavelengths to measure absorption coefficients [12, 13]. Although modern methods [14, 15] address these problems using learning-based algorithms, traditional methods are highly sensitive to wavelength selection. [16] used the same set of wavelengths as used in a conventional pulse oximeter; on the other hand, Mannheimer et al. [17] and Zonios et al. [18] used some other set of wavelengths. Again, Nitzan et al. [19] used three specific wavelengths instead of two.

Some researchers have used specialized cameras with specific characteristics, while others have used mobile phones or video cameras to capture the signal. For example, Yoshizawa et al. [20] used RGB cameras for noncontact oxygen saturation, but Complementary metal-oxide-semiconductor (CMOS)-based cameras later gained popularity.

Camera-based methods also have a variety of choices in selecting the signal-capturing region. Although the most common choice is the facial region of the subject because it has a relatively thin dermis, it has also been observed that palms [1, 21], irises [22], and even eyeballs have been targeted as regions of interest (ROIs) for capturing the signal. Some researchers have selected

the esophageal region as the preferred site for measuring blood oxygen saturation.

Because the distance between the camera and the ROI is quite large, natural movements in the dataset result in motion artifacts. To solve the motion issue, researchers proposed different approaches. Some of them are Singular value decomposition (SVD), wavelength mixing, a novel fusion technique [23], noise-resistant signal generation, an inversion technique, the application of the smoothed pseudo-Wigner-Ville distribution, a novel in vitro model, a frequency-domain approach, etc.

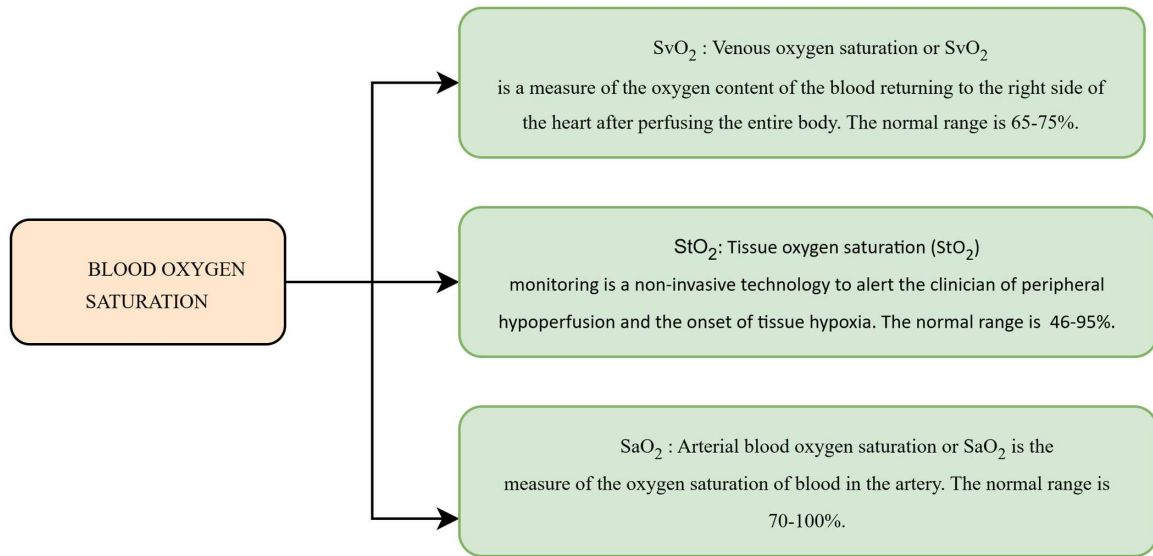
It is also observed that human skin undergoes some degree of strain. In the work of Wang et al. [24], they designed a stretchable optical sensing patch system to measure  $SpO_2$ .

Given the large number of methods based on different ideas, one can expect diverse approaches, evaluation parameters, accuracy metrics, etc., for solving the problem. Moreover, due to variations in datasets, evaluation schemes, and methodologies across papers, it can be difficult to understand the limitations, scope, and significance of the methods. As there is no review paper in the literature that bridges the gap between open challenges and state-of-the-art techniques. This observation motivated us to propose a survey to analyze the methodology, development, scope, and limitations to understand the approaches systematically.

## 3. Proposed Survey

Although blood oxygen saturation is directly related to HR and various important physiological parameters, including metabolism, which are largely dependent on the oxygen saturation level, there is no survey paper for measuring blood oxygen saturation. A study on blood oxygen saturation can indicate hypoxic symptoms and respiratory function and can detect COVID-19. This is because, in COVID patients, oxygen saturation can drop significantly without any signs. Hence, a study on blood oxygen saturation can help develop a better medication system and inspire new research opportunities, improving existing methodologies by overcoming their limitations. Depending on the objectives, there are various methods for measuring blood oxygen saturation levels. Various widely used methods for measuring blood oxygen saturation are shown in Figure 3. Similarly, the blood oxygen parameter measurement and its usage are listed in Table 2. Among

**Figure 3**  
**Different methodologies to measure blood oxygen parameters**



**Table 2**  
**Different types of blood oxygen parameter measurement**

| Oxygen measurement methods                                                   | Usage/importance                                                                                                 |
|------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------|
| SvO <sub>2</sub>                                                             | It helps to determine whether the cardiac output and oxygen delivery are high enough to meet the patient's needs |
| StO <sub>2</sub>                                                             | It helps to determine access to peripheral arterial disease                                                      |
| SaO <sub>2</sub> (SpO <sub>2</sub> is an approximation of SaO <sub>2</sub> ) | It provides information on the adequacy of respiratory function                                                  |

the three, arterial blood oxygen saturation measurement is the most popular, as it provides valuable insights into respiratory and metabolic function.

A brief theory has been discussed, which provides the basic foundation for the operation of the oximeter. After classification, for each class, existing methodologies and their gradual improvements have been discussed, followed by both qualitative and quantitative performance analysis. The drawbacks of each class and their limitations in discussion motivate the study of the next sections. The survey plan is shown in Figure 4.

#### 4. Working Principle of a Pulse Oximeter

The standard approach for measuring blood oxygen levels is a gas chromatograph. However, this method is invasive and requires collecting blood samples and then chemical analysis. This makes it unsuitable for continuous monitoring of blood oxygen saturation in various acute clinical conditions. Our blood carries red blood cells, which contain hemoglobin. This hemoglobin gives our blood its red color. Hemoglobin contains four O<sub>2</sub> carrier sites. When all of these O<sub>2</sub> carrier sites carry O<sub>2</sub> molecules, the hemoglobin becomes bright red. This configuration is known as oxygenated hemoglobin (HbO<sub>2</sub>). Alternatively, when these O<sub>2</sub> carriers are empty, that is, do not carry O<sub>2</sub> molecules, that configuration is called deoxygenated hemoglobin or Hb. This deoxygenated hemoglobin is darker red. The following graph (Figure 5 [25] shows the molar extinction for different wavelengths of light).

Figure 5(a)–(b) [25] shows that absorption of light at different wavelengths differs significantly between oxygenated and deoxygenated hemoglobin. Oxygenated hemoglobin absorbs more IR light and allows more red light to pass through, in contrast to deoxygenated hemoglobin, which allows more IR light to pass through and absorbs more red light. Based on this property of difference in absorption in different wavelengths, a ratio of pulsatile signal normalized by nonpulsatile signal at different wavelengths is generated. This is called the ratio of ratios (ROR). It has been observed that this ROR has a linear relationship with SpO<sub>2</sub>. To derive formally [25], let the total hemoglobin concentration be tHb. The normal hemoglobin includes RHb and O<sub>2</sub>Hb, while the dyshemoglobins include carboxyhemoglobin (COHb), methemoglobin (MetHb), and sulfhemoglobin (SHb). The total hemoglobin concentration (tHb) can hence be defined as in Equation (1).

$$tHb = O_2Hb + RHb + MetHb + COHb + SHb \quad (1)$$

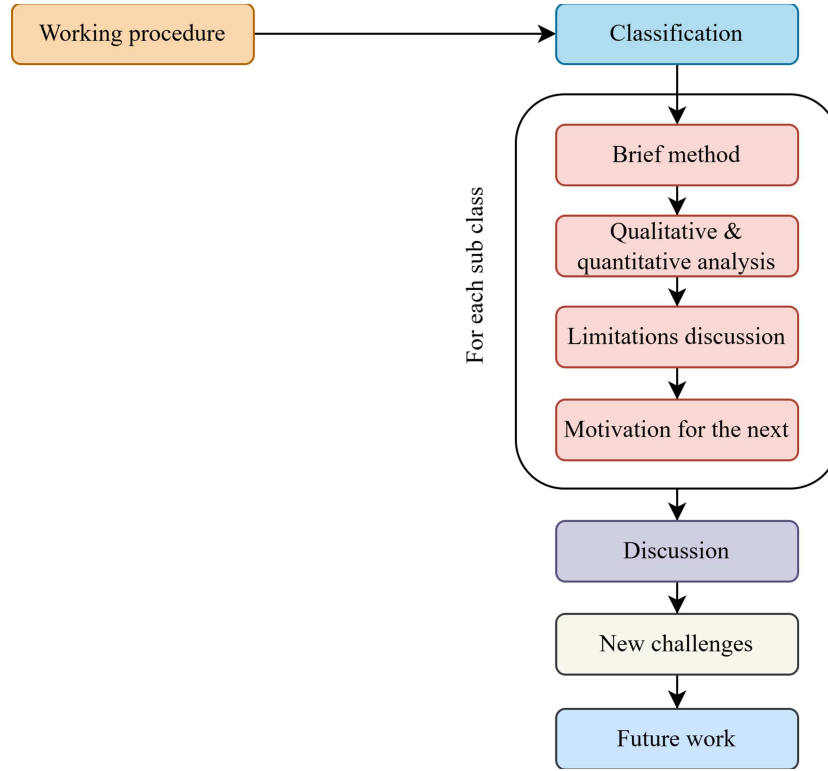
As SHb is rare and only oxygen-carrying hemoglobin is considered for oxygen saturation measurement, S can be written as Equation (2).

$$S = \frac{HbO_2}{HbO_2 + RHb} \quad (2)$$

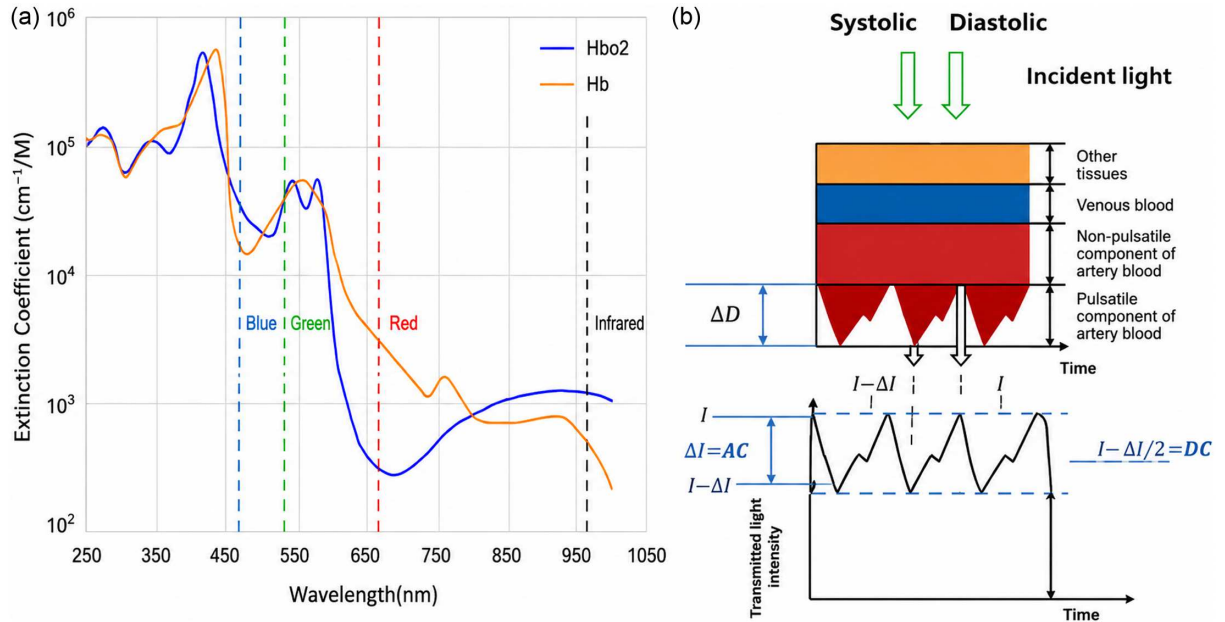
The light absorption, A, of the blood sample is defined by the Beer–Lambert law as defined in Equation (3).

$$A = \log \left( \frac{I_0}{I} \right) = E.C.D \quad (3)$$

**Figure 4**  
Pipeline of the proposed survey



**Figure 5**  
(a) Extinction coefficient vs wavelength graph, (b) optical model of human finger



where  $I_0$  is the incident light intensity and  $I$  is the transmitted intensity.  $E$  is the extinction coefficient, where  $I_0$  is the incident light intensity,  $I$  is the transmitted light intensity,  $E$  is an extinction coefficient (dL/g/cm),  $C$  is the concentration (g/dL), and  $D$  is the thickness (cm). The structure of the finger consists of tissue, venous blood, and arterial blood. The changes in the systolic and diastolic phases of arterial blood are shown as the

thickness,  $\Delta D$ , of arterial blood. The transmitted light intensity difference between the systolic and diastolic phases is expressed in  $\Delta I$ . Thus, the absorbance difference  $\Delta A$  is expressed by the Beer–Lambert law as defined in Equation (4) and Equation (5).

$$\Delta A = \log \frac{I}{I - \Delta I} = Eh.Hb. \Delta D \quad (4)$$

$$= \frac{\Delta I}{\left(I - \frac{\Delta I}{2}\right)} = \frac{AC}{DC} \quad (5)$$

where Hb (g/dL) is the hemoglobin concentration, Eh (dL/g/cm) is the extinction coefficient of Hb, and  $\Delta D$  (cm) is the change in the thickness of the arterial blood. At 660 and 940 nm, which are used for pulse oximeter measurements, the absorbance of other tissues in the blood is ignored, except for oxygenated and deoxygenated hemoglobin.

## 5. Classification

As discussed in the previous section, several methods can be used to measure arterial blood oxygen saturation. The methods work on different principles, with different natures and uses. Therefore, the methods can be classified into two major classes: contact-based and noncontact-based methods. The contact-based methods can be further divided into transmissive and reflexive measurements using the ROR approach. In the same way, noncontact-based methods can be further divided into ratio-based and deep learning-based methods. The classification hierarchy is shown in Figure 6.

## 6. Contact-Based Methods

Most conventional devices available today are contact-based pulse oximeters. This is used extensively in healthcare settings, such as hospitals and clinics, as well as by individuals to monitor oxygen saturation. In recent times of COVID-19, this has become the norm. This contact-based method for measuring blood oxygen saturation is mainly based on a principle called the ROR. The general steps common to most contact-based methods for oxygen level measurement are shown in Figure 7.

In this approach, the pulsatile blood absorption coefficient is normalized by the absorption coefficient of nonpulsatile

blood. This is measured at two wavelengths: for one, the absorption coefficient varies widely, and for the other, it does not. This is the principle that is used to develop contact-based methods. This can further be classified into two sub-groups depending on the methods by which the emitted light gets captured, namely, (i) transmittance measurement and (ii) reflectance measurement.

**Transmittance measurements:** This is the oldest and most widely implemented method for measuring blood oxygen saturation.  $SpO_2$  can be assessed noninvasively by pulse oximetry, which uses photoplethysmographic signals at two wavelengths in the red and IR regions [19]. However, various authors have chosen different sets of wavelengths. The subject's finger is inserted into a finger clip whose interior is kept as dark as possible to eliminate interference from ambient light. Two LEDs with wavelengths of 660 and 940 nm are mounted on the upper part of the finger, and a sensor that captures the transmitted light is placed beneath the finger. When illuminated, the light generated from the LEDs passes through the finger and gets transmitted to the sensor. The transmitted signal can be classified into two components: dynamic or varying parts, such as alternating current (AC), and static parts, such as direct current (DC). AC is the absorptive coefficient for pulsatile blood in an artery (this changes with each pulse), and DC (this does not vary) is the absorptive coefficient for nonpulsatile blood from the skin layer, venous blood, and nonpulsatile arterial blood. The sensor senses absorption at different wavelengths, and finally, the ROR is measured as defined in Equations (6) and (7).

$$R = \frac{\frac{AC(\lambda_1)}{DC(\lambda_1)}}{\frac{AC(\lambda_2)}{DC(\lambda_2)}} \quad (6)$$

$$SpO_2 = k.R + b \quad (7)$$

Figure 6  
Classification diagram

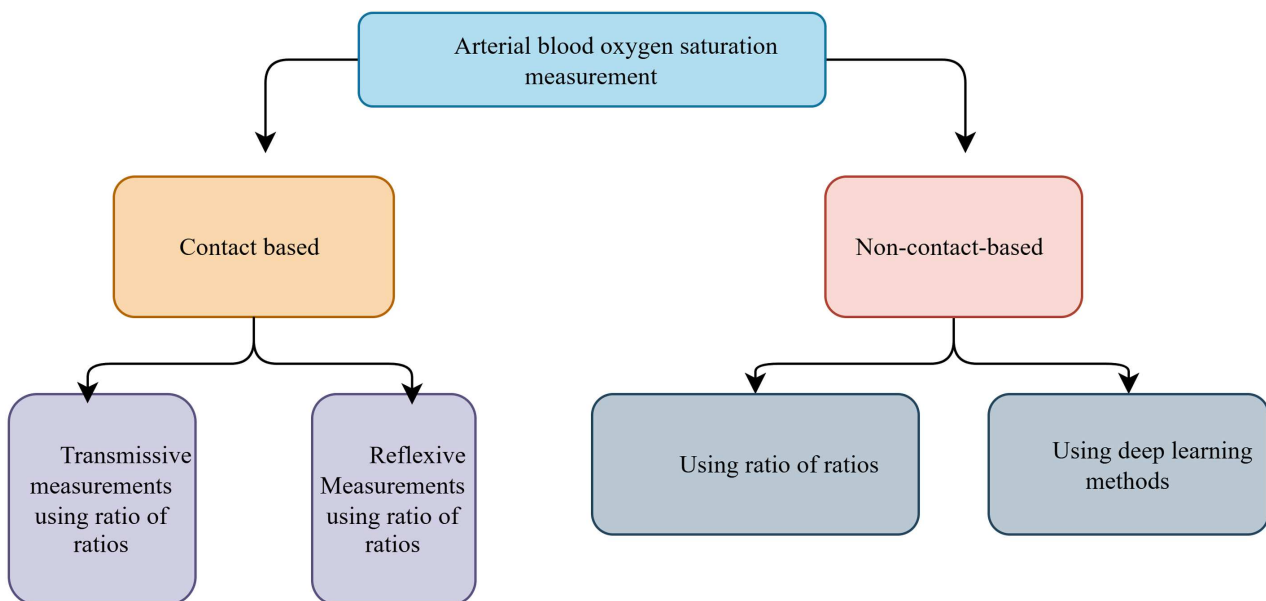
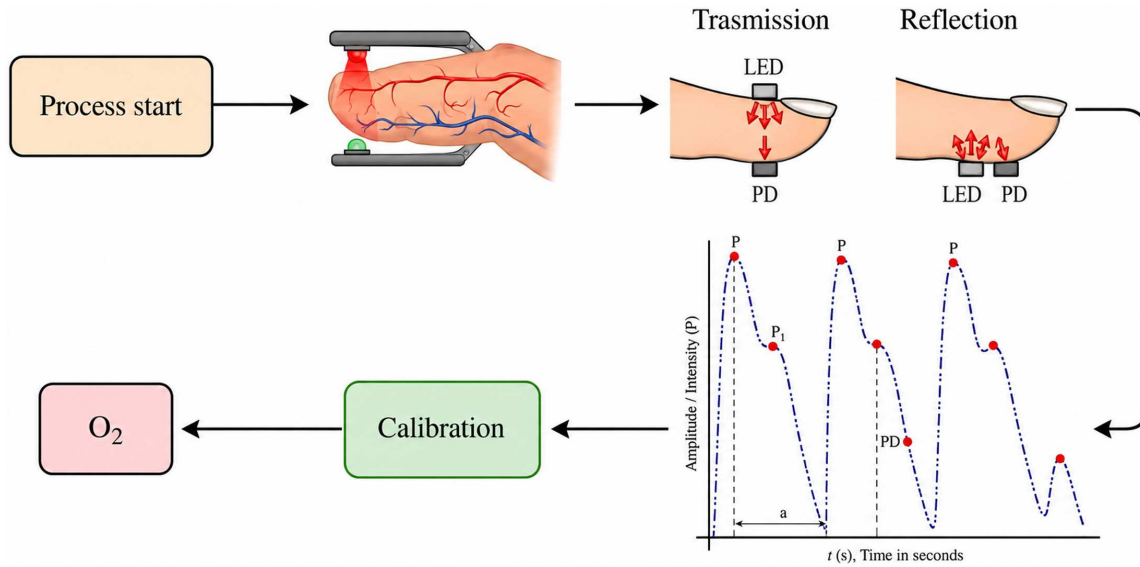


Figure 7  
General block diagram for the measurement of blood oxygen saturation using contact-based methods



The above equations are known as empirical calibration equations. In a conventional pulse oximeter, the empirical calibration equation for  $\text{SpO}_2$  estimation is derived from the data obtained from a large group of healthy nonsmoking young volunteers. Manufacturers of pulse oximeters generally claim an accuracy of 2%, evaluated by the standard deviation (SD) of the differences between  $\text{SpO}_2$  and  $\text{SpO}_2$ , measured simultaneously in healthy subjects. However, an SD of 2% corresponds to an expected error of 4% (2 SDs) in 5% of examinations, consistent with the 3–4% error reported in clinical studies [8]. Although this method works in various situations, the basic problem lies in calibration, which is largely dependent on the sample choice, and this may vary.

**Usage of logarithm:** In reference [16], it was shown that the use of the natural logarithm removes the influence of source intensity, detector sensitivity, and patient-dependent parameters from the AC part of the PPG signals. They also demonstrated that this implementation of the natural logarithm makes the parameter of the AC part alone sufficient to compute  $\text{SpO}_2$  values without calibration or constants derived from volunteer data.

**Fuzzy logic usage:** In reference [12], the authors implemented it to avoid calibration. In their method, the ROR value is calculated from sensor signals and then used as input to the fuzzy logic, and  $\text{SpO}_2$  is calculated. They also created a linear relationship between  $\text{SpO}_2$  and  $R$  values, using absorption coefficients, by linear regression, and compared it with  $\text{SpO}_2$  values calculated by the fuzzy logic method.

**Three-wavelength technique:** Nitzan et al. [19] proposed a three-wavelength technique that does not require calibration, thereby making the model more robust. According to their assumption, if the two wavelengths used to measure oxygen saturation are approximately equal, then their ratio approaches 1, eliminating the need for a calibration procedure. They used wavelengths of 767 nm and 811 nm. The  $\text{SaO}_2$  value was somewhat lower than that obtained with the commercial pulse oximeter. But their accuracy increased when the ratio was changed from 1 to 0.97.

**Different wavelength choice:** Recently, pulse oximetry has been used in the obstetrical delivery room to monitor the fetal

oxygen status during labor and delivery. The normal range for the fetus is generally lower, at 20–70%. Because conventional pulse oximetry operates in the 70–100% range, it requires careful monitoring to measure oxygen accurately. Mannheim et al. [17] carried out a comprehensive study where they found that numerical modeling with 735 and 890 nm gives better and more consistent results than using 660 and 900 nm.

**Broader oxygen saturation range:** Zonios et al. [18] improved the accuracy and reliability of the transmissive pulse oximeter for the lower saturation situation. They have shown that the uncertainty that lowers the accuracy is mainly caused by the tissues with low saturation. In their paper, they represented this uncertainty introduced by the tissue using a single parameter and showed how this formalization can help with better calibration in the lower range.

In Table 3, it can be observed that to measure relative normalized light absorption ratios, different researchers have selected different wavelengths. The main motivation for selecting a specific wavelength is that PPG measurements at that wavelength provide significant insight into the contribution of arterial blood to the total light absorption. Not only do conventional pulse oximeters use 660 nm and 940 nm, but other researchers also use the same set of oxygenated blood to absorb higher energy in the IR region than in the red region. Similarly, deoxygenated blood absorbs more in the red region and relatively less in the IR region. This increases signal strength, which helps measure oxygen saturation. However, this method requires calibration. It was shown that three wavelengths in the near-IR region can address calibration needs. Not only that, Mannheim et al. [17] and Zonios et al. [18] have shown that the consistency and ambiguity arising from inhomogeneity can be addressed using different sets of wavelengths. Table 4 presents the strengths, weaknesses, criteria, and applicability of transmittance pulse oximeters, and Table 5 provides a quantitative analysis. It has been observed that all the methods apply only to peripheral regions, such as the finger and earlobe. So, it might be challenging in some cases where peripheral sites are not available. Moreover, perfusion, the volumetric flow rate per unit volume of tissue, needs to be higher for these methods to be deployed.

**Table 3**  
**Variation in selecting the wavelength for transmissive measurement**

| Method              | No. of wavelengths used | Wavelength selection   | Advantages of wavelength selection                                                             |
|---------------------|-------------------------|------------------------|------------------------------------------------------------------------------------------------|
| Commercial oximeter | 2                       | 660 nm, 940 nm         | Conventional                                                                                   |
| [12]                | 2                       | 660 nm, 940 nm         | Conventional                                                                                   |
| [16]                | 2                       | 660 nm, 940 nm         | Conventional                                                                                   |
| [19]                | 3                       | 660 nm, 767 nm, 811 nm | Adding 3rd wavelength removes motion artifacts and gives more robust results                   |
| [17]                | 2                       | 735 nm, 890 nm         | Better, more consistent results have been observed than with conventional wavelength selection |
| [26]                | 2                       | 660 nm, 890 nm         | –                                                                                              |
| [18]                | 2                       | 730 nm, 940 nm         | Uncertainty due to tissue inhomogeneity is removed by using these two wavelengths              |

**Table 4**  
**Qualitative analysis of methods based on transmission phenomena**

| Method                       | Type       | Objective                                                                                | Strength                                                                                               | Weakness                                                                                                            | Perfusion (0.2–20%, 0.2 is considered low and 20 is high) |
|------------------------------|------------|------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------|
| Normal Pulse oximeter (1996) | Peripheral | Noninvasive measurement of blood SpO <sub>2</sub>                                        | Measures within the 2% error limit within the 70–100% range                                            | Cold or hypotension weakens signal strength, leading to measurement error                                           | High                                                      |
| [17]                         | Peripheral | A novel and different selection of wavelengths                                           | Sudden changes in tissue oxygen saturation do not affect the accuracy                                  | –                                                                                                                   | High                                                      |
| [18]                         | Peripheral | Addresses the inhomogeneity of tissues, which is the cause behind inaccuracy             | Inhomogeneity is represented by a single parameter, thereby improving calibration                      | This method is semi-empirical. Hence, some parameters need to be calibrated with data                               | High                                                      |
| [19]                         | Peripheral | The application of three wavelengths rather than two in most of the conventional methods | Does not require calibration                                                                           | Though it has a strong theoretical background, the experimental verification is unclear in their method             | High                                                      |
| [12]                         | Peripheral | Usage of fuzzy logic for estimating SpO <sub>2</sub> value                               | Does not require calibration, as most conventional methods do, and has yielded more consistent results | Though they proposed an improvement over the regression model, they did not provide sufficient numerical validation | High                                                      |

**Limitations of transmittance-type oximetry:** Although most available and popular oximeters fall into this category, it has the following limitations at the design and application levels.

- 1) Transmittance pulse oximeters are primarily used on extremities, such as fingertips, earlobes, and toes. Moreover, its accuracy depends upon vasoconstrictors, perfusion level, incorrect probe placement, motion artifact, etc. [18].
- 2) In obstetrics, this method is not applicable because there are no transilluminable fetal parts.
- 3) This method largely requires the optical paths for both wavelengths to be the same. But this might not hold true in every situation.

Table 5  
Quantitative analysis of methods based on transmission phenomena

| Method                       | Datasets                                           | Metrics for accuracy measurement                           | Results                                                |
|------------------------------|----------------------------------------------------|------------------------------------------------------------|--------------------------------------------------------|
| Normal pulse oximeter (1996) | –                                                  | RMS accuracy (given by Food and Drug Administration (FDA)) | Acceptable within 2–3% of the arterial blood gas value |
| [18]                         | Nine ovine fetuses at 0.9–0.95 gestation were used | RMS between SpO <sub>2</sub> and SaO <sub>2</sub>          | 13.3 for empirical calibration, 8.7 for given data     |

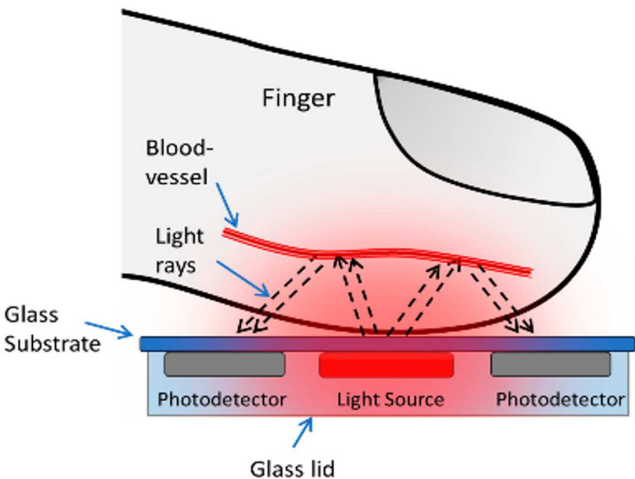
- 4) This method is very sensitive to light interference.
- 5) Moreover, if the patient’s finger is pressed hard, the optical path changes, and, according to Beer–Lambert’s law, the absorption is directly proportional to the optical path length.
- 6) Calibration is one of the biggest issues for transmissive measurements. Almost all oximeters rely on a calibration equation that works specifically for a selective set of samples.
- 7) This method measures the oxygen saturation for a specific point; it can be considered a pointwise measurement. But when a large region’s oxygen saturation count is needed, this method can’t be applied.
- 8) Being contact in nature, it is not suitable for patients in critical condition, such as infants, burnt patients, or cases where physical contact with the device causes significant discomfort. Almost every oximeter based on transmissive measurement is designed for use only on fingertips or earlobes.
- 9) Although conventional pulse oximeters achieve high accuracy for SaO<sub>2</sub>, their performance is severely affected at lower oxygen saturations due to nonlinear optical absorption and scattering by red blood cells and other optically dense tissues. To circumvent this inherent disadvantage, reflectance pulse oximeters for lower SaO<sub>2</sub> measurements have been developed [27]. Since the SaO<sub>2</sub> of the fetuses will drop below 70% during delivery, reflectance pulse oximeters that can measure lower SaO<sub>2</sub> values with greater accuracy are needed.

This limits the scope of transmissive oximeters because, in many critical or sensitive cases, they cannot be a useful solution. For example, in neonates, it is not possible to use an oximeter on the finger or earlobe. Hence, a reflexive oximeter is much more usable. As it works on the principle of reflection, it can be used in diverse critical places.

**Reflectance measurements:** The reflective measurements differ from the previous transmissive measurements. In reflectance pulse oximetry, the probe emits IR and red light, which passes through blood vessels and tissues. This gets reflected by the underlying bone and is detected at the level of the light-emitting electrodes. Figure 8 shows the basic construction of the reflectance pulse oximeter [28]. In general, a reflection pulse oximeter is a finger clamp similar to a transmissive pulse oximeter, connected to a handheld mobile device. In contrast, a reflective pulse oximeter is not dependent on the perfusion index or the thickness of the application area. There are also other sites, such as the forehead, chest, and wrist, from which a reflective pulse oximeter can capture a PPG signal. However, since the method is based on reflection, there is a high risk that ambient light will interfere with the selected light at specific wavelengths. As a result, the absorption coefficients of oxygenated and deoxygenated blood differ significantly, making it difficult to calculate blood oxygen levels.

It has been observed that reflectance oximetry captures signals that are substantially weaker than PPG signals compared to those of transmittance oximetry [29]. With light-emitting and

Figure 8  
The basic construction of a reflectance pulse oximeter



light-sensing sensors on the same side, backscattering occurs, significantly diminishing signal strength. Various attempts have been made to minimize exposure to ambient light, including specific shields that allow light of certain wavelengths. This prevents the mixing of unwanted wavelengths with the specifically required wavelength. In general, transmissive pulse oximeters measure blood oxygen saturation in a very limited area of the skin.

**A broader range of oxygen saturation:** [30] took a new approach to measure arterial oxygen saturation for a broader area. Normally, in the case of reflectance pulse oximetry, the reflected signal gets very weak in comparison to the transmitted signal by a range of 1/10 times. Hence, it becomes very difficult to measure amplitude variation. To enhance the reflected amplitude and remove the effect of tissue inhomogeneity, they used 10 LED chips per wavelength, mounted symmetrically at a radial separation of 7 mm around a photodiode chip. A wavelength of 730/880 nm was used to measure a broader SaO<sub>2</sub> range from 100% to 30%. The relationship between wavelength selection and SaO<sub>2</sub> sensitivity within the 660–800 nm range was determined using photon diffusion theory. The applicability of the new reflectance pulse oximeter sensor to various body regions, such as the chest wall, can expand its applications.

**Time-domain image processing:** The time-domain processing algorithm [31] is used to enhance the accuracy of real-time detection. This study may help design low-cost, portable devices for home healthcare applications. The method also improved the extraction algorithm based on the differential threshold method and demonstrated its feasibility and accuracy. They have designed a highly integrated chip that contains a blood oxygen sensor, a front-end analog sensor, a microcontroller unit (MCU), a power management block, and a Bluetooth module.

**Photodiode:** [32] developed a reflective pulse oximeter where the LED transmission unit and photodiode receiving units are on the same side. To switch between red and IR LED lights, the duty cycle was set to 50% with a switching frequency of 500 Hz, generating a pulse-width modulation signal from the MCU. Then, each reflected light beam was converted to an electrical signal, which was subsequently amplified with a gain of 100.

**Maximizing signal-to-noise ratio:** [33] implemented the same idea of ratio-based measurements. But instead of backscattering light, they captured the reflected light. They have studied the maximum signal-to-noise ratio (SNR) for measuring oxygen saturation by comparing the wavelengths at which oxygenated and deoxygenated hemoglobin exhibit the greatest absorption.

**Stretchable optical patch:** Human skin undergoes an average of 30% strain. This may lead to miscalculation with conventional methods. [24] designed a serpentine stretchable optical patch to overcome that problem. The patch adopted a serpentine stretchable interconnection between the optical sensor and the microcontroller. This can withstand 35% stretch and is therefore suitable for any type of skin tension. They have achieved 2% sensitivity.

**Transabdominal fetal oximetry:** Fetal oxygen saturation is one of the most important and suitable measures for fetal distress. But current fetal monitoring technology is still too far from providing a metric to physicians regarding fetal well-being, which leads to degraded patient outcomes. [34] designed transabdominal fetal oximetry to overcome this issue by measuring fetal SpO<sub>2</sub>. They tested their method on an in utero hypoxic fetal lamb model and performed controlled experiments. Their results showed a strong

correlation with the gold standard, with an Root Mean Square Error (RMSE) of 6.37%. Table 6 shows the strengths and weaknesses of the methods based on reflectance measurement. Table 7 presents a quantitative analysis of these measurements. It is noted that, as reflectance methods do not require the signal receiver to be placed opposite the emitter, one constraint of transmittance measurement is that the peripheral site must be released. Moreover, as the emitted signal travels over a shorter distance, a medium/low perfusion index can yield good accuracy in the reflectance pulse oximeter, which was not possible in the transmittance pulse oximeter.

**Limitations of reflectance-type oximetry:** Methods based on reflection are much more flexible to use and, in most cases, do not require the perfusion index to be high. As reflectance-type oximeters are easy to use at any skin position rather than only on fingertips etc., they have gained a lot of interest in the research community. But there are also some limitations to this method, which are listed in the following.

- 1) As the methods are based on reflection, which occurs when the light gets reflected on the bone, the reflected signal intensity is quite low (approximately 10 times lower than that of the transmissive signal). Hence, it is more prone to noise.
- 2) Moreover, the sensor and emitter residing on the same side create interference, making the quality of the signal worse. To solve this problem, the intensity of the incident light is made higher.
- 3) This solves the problem partially, but another problem arises, which is to increase the intensity, these devices consume greater

**Table 6**  
**Qualitative analysis of methods based on reflection phenomena**

| Method | Objective                                                                        | Nature      | Perfusion index | Strength                                                                                            | Weakness                                                                                                 |
|--------|----------------------------------------------------------------------------------|-------------|-----------------|-----------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|
| [30]   | Usage of multiple LEDs to enhance or broaden the area of the measuring site      | Noninvasive | Low             | Multiple illuminating-source implementations measure the saturation over a broader area of the skin | Signal strength is 10 times weaker than transmittance oximetry                                           |
| [33]   | Maximizing signal-to-noise ratio                                                 | Noninvasive | –               | Robust to patients with respiratory failure, too                                                    | Needs calibration                                                                                        |
| [31]   | Usage of the domain processing algorithm                                         | Noninvasive | Low             | Low-cost, portable design                                                                           | –                                                                                                        |
| [32]   | Investigation of AC amplitudes and DC offset for the measurement of blood oxygen | Noninvasive | Low             | ROR increases with decreasing oxygen saturation                                                     | More sensitive to DC instability. Moreover, proper experimental data are missing                         |
| [24]   | Stretchable optical sensor                                                       | Noninvasive | Low/moderate    | Applicable even when the skin is under tension                                                      | There is a tradeoff between LED current and PDMS coating thickness                                       |
| [34]   | Transabdominal fetal oximetry to measure oxygen saturation in the fetus          | Noninvasive | Low/moderate    | Can measure fetal blood oxygen saturation                                                           | The model has been evaluated in the fetal lamb model; hence, the human scenario is not well demonstrated |

**Table 7**  
Quantitative analysis of methods based on reflection phenomena

| Method | Datasets                                    | Metrics                        | Results                                                                                                                          |
|--------|---------------------------------------------|--------------------------------|----------------------------------------------------------------------------------------------------------------------------------|
| [30]   | 30 adult volunteers with healthy conditions | Standard error                 | 2.11% (730/880 nm, 70–100%)                                                                                                      |
| [33]   | 26 volunteers                               | Correlation, SD, variance      | 0.98, 1.59, 2.54 (637/799 nm)<br>0.98, 1.53, 2.34 (637/900 nm)<br>0.99, 1.41, 2.00 (658/799 nm)<br>0.99, 1.43, 2.05 (658/900 nm) |
| [31]   | Volunteers aged 24–26                       | % SpO <sub>2</sub> measurement | 97.135% (forehead)<br>96.328% (temporal)<br>96.669% (arm)                                                                        |
| [24]   | –                                           | % accuracy                     | 2%                                                                                                                               |
| [34]   | –                                           | RMS error                      | 6.37%                                                                                                                            |

power, hence not suitable for a carry-on device to measure the oxygen saturation level.

- 4) Moreover, tissue inhomogeneity creates an anomaly. In the transmissive process, the incident light travels through the tissue just one time. But in the reflective process, it travels twice: first, during the incident, and second, during the reflectance. As the tissue structure is not optically homogeneous, it introduces an anomaly in detecting the pulsatile and nonpulsatile signals.

**Summary:** Contact-based methods (both the transmittance and the reflectance for measuring oxygen saturation) provide a quick and reliable measure of blood oxygen saturation and hence are widely used in medical care units. A pulsatile PPG signal normalized by the nonpulsatile component is used to measure the saturation. The similarity between the two types of contact-based measurement methods is that, in transmittance-type oximetry, the transmitted light is captured by the sensor on the opposite side of the emitter sensor. In contrast to this, in a reflectance oximeter, the emitter and receiver both stay on the same side. As in transmittance measurements, the light travels a relatively greater distance, and lower perfusion index and tissue inhomogeneity are two major problems that led to the development of reflectance-type oximeters. Because the emitter and receiver are on the same side, the light needs to travel a shorter distance; hence, these methods are insensitive to the aforementioned problems. But both methods implement a major set of ratios that require calibration, and this calibration is the source of errors and sample bias, reducing the applicability of the methods across the global range. In addition, in some critical cases, the contactless nature can restrict the applicability of these methods. For these reasons, researchers tend to find methods to measure blood oxygen saturation in a noncontact manner.

## 7. Noncontact-based Methods

With recent advances in imaging systems and camera sensors, significant improvements have been seen in biomedical image analysis. One such is photoplethysmography, which is also known as PPG. In contrast to contact-based models, which require physical contact with the sensor, noncontact methods leverage this problem. The noncontact method primarily relies on a video-based procedure to measure blood oxygen saturation. The common steps in noncontact-based methods for measuring oxygen saturation are shown in Figure 9. Considering methods of measurement, we can divide this into two classes, namely,

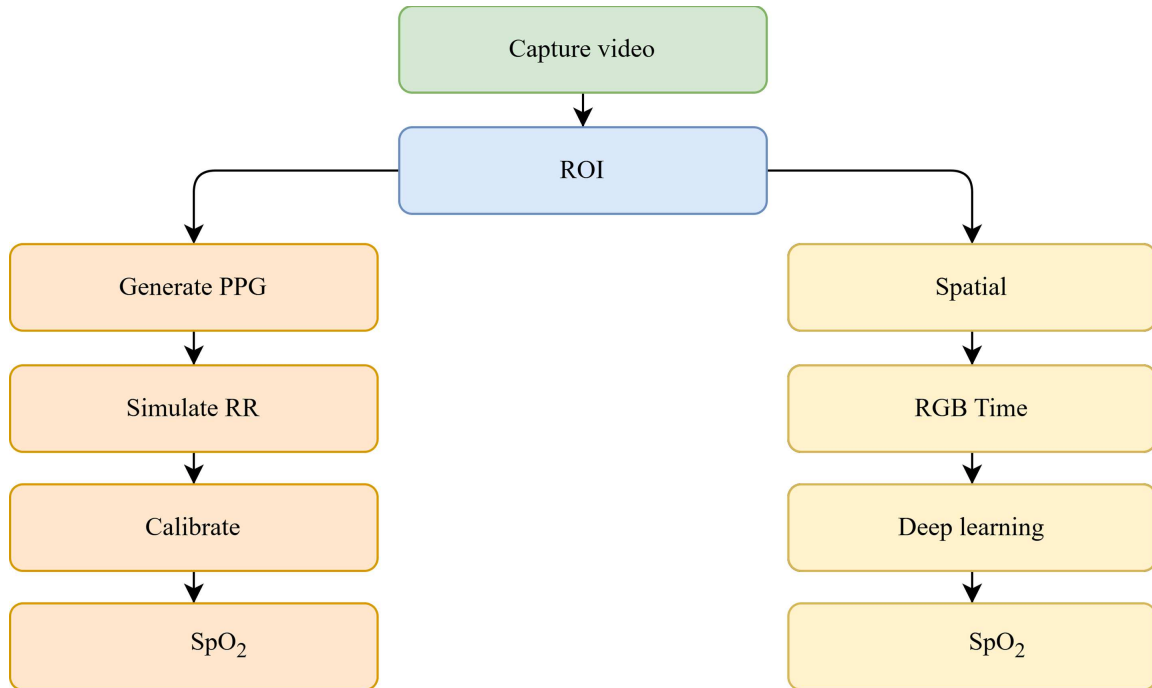
- (i) ROR-based approach and (ii) deep learning-based approaches, as shown in Figure 9.

**The ROR-based approaches:** To our knowledge, most of the research conducted on noncontact methods is based on video processing data. The basic idea behind these approaches is rather simple. It emulates the idea that, while a person continues respiration, their arteries and veins contain oxygenated and deoxygenated blood during systole and diastole, respectively. Because oxygenated and deoxygenated blood have different absorption coefficients at different wavelengths, the skin color changes slightly during systole and diastole. Video data sequentially capture this information; it is possible to retrieve useful information from the video data. The basic pipeline for video-based oxygen saturation methods includes capturing videos, specifying ROIs, and then from these regions, PPG signals are obtained. Now this PPG signal is further processed and a simulation of the ROR is used to measure oxygen saturation. But the problem arises as in this method, the near-monochromatic light sources with known intensity are completely replaced by broadband light sources with unknown intensity. Moreover, these video sensors have a fairly low frame rate (30 Hz) [17]. The SNR of the SpO<sub>2</sub> value depends on the choice of wavelengths. To emulate dual wavelengths, namely, red and IR, in the visual spectrum, the different channels are used to obtain a PPG signal [35].

**Using a CCD camera:** The work of Kong et al. [27] showed that a video-based PPG signal, which uses reflection as a basic principle, receives a weak signal in the IR region, making it hard to calculate. But at 520 nm, not only are the absorption coefficients of HbO<sub>2</sub> and Hb equivalent. Then the curves change more gradually, making them quite suitable for blood-saturation measurement. To implement this idea, they used two CCD cameras, mounted with a narrow-band-pass filter to capture PPG signals at two different wavelengths (520 nm and 660 nm) in ambient lighting conditions. The test only covered a narrow SpO<sub>2</sub> range (97–99%). For practical applications, such as in clinical settings, it is necessary to measure SpO<sub>2</sub> over a wider range (at least 80–100%). Although they have used ambient light, their approach removes the limitation of the distance between the source and the subject. One of the 30 groups of data lies beyond the limits  $d - 1.96 \cdot Sd$  and  $d + 1.96 \cdot Sd$ . It indicates that the accuracy of the proposed noncontact measurement device can't reach the level required for clinical application.

**The facial region as ROI:** Bal [35] implemented averaging over pixels in the facial region, which is considered as ROI in the red and blue channels, to construct a PPG signal, and the ROR was used, but, in this case, mean and SD were used as

Figure 9  
Basic pipeline of a noncontact-based approach



DC and AC, respectively. The values of the constant parameters of the empirical equation were calculated using the best-fit linear equation between the oximeter reading and the ratio of the red and blue channels.

**Rectangular ROI:** Casalino et al. [36] tracked three rectangular ROIs in the forehead and cheeks and spatially averaged them to generate a PPG signal over the RGB channels. Their finite-impulse-response and chrominance methods remove high-frequency noise, motion, and illumination variation. Then, the most informative ROI is chosen using power spectral density. They used red and blue, AC as SD, and DC as the mean.

**Wavelength selection for SNR maximization:** Shao et al. [37] found that the combination of orange ( $\lambda = 611$  nm) and near-IR ( $\lambda = 880$  nm) provides the best SNR for the noncontact video-based detection method. This combination differs from that used in traditional contact-based  $\text{SpO}_2$  measurement, as the PPG signal strengths and camera quantum efficiencies at these wavelengths are more amenable to noncontact  $\text{SpO}_2$  measurement. When captured with a camera, the PPG waveforms are much weaker, and consequently, the measurement is more sensitive to distortions and noise.

**Implementation of SOSI:** Tsai et al. [26] introduced their Skin oxygen saturation imaging (SOSI) method using reflected images of skin tissue in the red and NIR spectral regions. The transcutaneous oxygen pressure ( $\text{TcPO}_2$ ) measurement is another noninvasive method for measuring the partial pressure of oxygen ( $\text{PaO}_2$ ) in the peripheral microcirculation system of the human body. They included this test in their study. As the level of  $\text{HbO}_2$  is determined using the level of  $\text{PaO}_2$ , the  $\text{SpO}_2$  and  $\text{PaO}_2$  levels can be compared simultaneously, and the relationship between the two levels in the blood can be transformed using the  $\text{HbO}_2$  dissociation curve. In their study, the  $\text{HbO}_2$  dissociation curve was modeled as a sigmoid function, and the relationship with the reference value was presented.

**Using iris as ROI:** Wang et al. [22] proposed a new approach to measuring 2D oxygen levels in blood using iris images. They developed a new calibration model that uses two appropriate red and near-IR wavelengths to estimate iris tissue blood oxygen levels.

**Channel selection and FFT:** Al-Naji et al. [38] focus on channel selection for obtaining the best signal from video-based data. Their Fast Fourier Transform (FFT) spectrum analysis on ICA output data indicated that the red and green channels were most suitable for obtaining most of the information. To reduce the noise, after the automatic identification of facial ROIs, they have implemented Ensemble Empirical Mode Decomposition (EEMD) and Independent Component Analysis (ICA) to decompose the signal effectively from noise. Some researchers presented a model to predict  $\text{SpO}_2$  using a mobile phone camera and flashlight. The main challenge is that the phone's flashlight does not emit light above 760 nm. Therefore, the focus of their model is the range from 600 nm to 779 nm and the one that maximizes the angle of the relationship curve between red and IR.

**The multichannel ROR using a smartphone camera:** The authors in [1] used a smartphone camera to measure blood oxygen saturation by implementing multichannel ROR-based methods. Unlike most approaches, they have considered the R, G, and B channels rather than using only two. As the SNR is relatively low in smartphone video, they have designed an adaptive bandpass filter centered on the HR frequency rather than using the SD or peak-to-valley amplitude as the AC pulsatile value.

**Eulerian video magnification:** Physiological and optical properties change with each cardiac cycle, which is very subtle and incomprehensible to the human eye. To address this kind of limitation, [39] proposed the Eulerian video magnification technique, in which EVM recognizes temporal changes that are imperceptible to the human eye. In this method, they proposed a standard video sequence as input and applied spatial decomposition followed by temporal filtering to the frames. The resulting signal is

then amplified to reveal hidden information. Their accuracies in the two experiments are 0.99% and 1.09%, respectively, both of which are below 2%.

Table 8 summarizes the strengths and weaknesses of non-contact methods based on ratios to measure blood oxygen saturation. Due to its noncontact nature, the distance between the signal-capturing instrument and the subject introduces noise, adversely affecting the measurement. But many researchers have cleverly tackled this problem, as listed in Table 6. In Table 9, datasets, accuracy, metric, and accuracy measures are listed for noncontact ROR methods.

**Limitations of ratio-based approaches:** One of the most widely applied and well-researched methods for noncontact oxygen

saturation measurement is the ROR approach. Although these noncontact methods can estimate SpO<sub>2</sub> without direct contact with the patient's body, they have some limitations.

- 1) These methods are mostly based on empirical equations that need to be calibrated. Hence, the calibration values depend on the choice of sample. A large sample generalizes more, though most studies used fairly small samples, limiting their applicability to a narrow range of subjects.
- 2) Because cameras capture PPG signals, there is always a distance between the camera and the subject. As a result, relative motion gives rise to motion artifacts, which degrade signal quality. To overcome this problem, various techniques such as

**Table 8**  
Qualitative analysis of methods based on the ratio of ratios

| Method | Objective                                                                        | Nature      | Strength                                                                               | Weakness                                                                         |
|--------|----------------------------------------------------------------------------------|-------------|----------------------------------------------------------------------------------------|----------------------------------------------------------------------------------|
| [27]   | Regular lighting condition                                                       | Noninvasive | Works in ambient lighting conditions, distance factor is removed                       | Motion artifact is a major limitation                                            |
| [35]   | Dual tree complex wavelet transforms for removing noise from ROIs                | Noninvasive | Robust to motion artifact, Artificial scattering                                       | The higher error rate in low saturation conditions                               |
| [37]   | Maximize SNR for better and consistent results                                   | Noninvasive | Robust signal noise                                                                    | Extreme lower values raise an anomaly                                            |
| [36]   | Real-time facial ROI tracking from video data                                    | Noninvasive | Relatively faster and easier to use                                                    | Experimentation and calibration were conducted on a comparatively small sample   |
| [26]   | Optical density between reflected and incident light                             | Noninvasive | Stable measurement of the full region                                                  | Includes a heating step that creates discomfort                                  |
| [24]   | Oxygen density measurement from iris tissue and a novel calibration method       | Noninvasive | A 2D reflectance image has been studied                                                | –                                                                                |
| [39]   | The Eulerian video magnification technique is used to calculate SpO <sub>2</sub> | Noninvasive | Captures minor spatial and temporal signals using EVM and calculates oxygen saturation | –                                                                                |
| [38]   | Best informative channel detection and noise reduction                           | Invasive    | Consistent and robust to noise                                                         | Motion artifact                                                                  |
| [1]    | Measures SpO <sub>2</sub> with a mobile phone                                    | Noninvasive | An adaptive bandpass filter centered on HR frequency enhances the accuracy             | The signal generated in this smartphone-based video data generally has a low SNR |

**Table 9**  
Quantitative analysis of methods based on the ratio of ratios

| Methods | Datasets                                                                                     | Metrics used for accuracy measurement | Result                                         |
|---------|----------------------------------------------------------------------------------------------|---------------------------------------|------------------------------------------------|
| [27]    | Self-collected video dataset of 30 volunteers of ages between 18 and 54                      | Bland–Altman plot                     | 1 among 30 lies outside of the limitation band |
| [35]    | Self-collected data from six healthy and 3 Pediatric Intensive Care Unit (PCIU) participants | Correlation                           | Greater than 0.81                              |
| [36]    | Self-collected data of 21 participants                                                       | Average error                         | Less than 2%                                   |
| [37]    | –                                                                                            | Correspondence                        | 98%                                            |
| [26]    | Self-collected dataset of people of age group 30–40                                          | Absolute error                        | Less than 1%                                   |
| [24]    | –                                                                                            | Maximum error                         | Less than 0.4                                  |
| [39]    | –                                                                                            | RMSE                                  | 0.99%, 1.09%                                   |
| [38]    | –                                                                                            | SSE, Mean Absolute Error (MAE), RMSE  | 2.72, 3.02, 3.62                               |
| [1]     | –                                                                                            | MAE                                   | 1.26%                                          |

- ROI tracking, SVD, etc., have been applied, but none of them is fully able to solve it.
- 3) These methods generally work for a range of 70–100%. However, it has been observed that in many cases, the oxygen level falls below this range. In those situations, these methods are not fully reliable to be used for clinical applications.
  - 4) There is also an approach that involves heating the skin to a specific temperature to increase blood flow and ensure accurate measurement. However, this is a serious limitation as heating might not be applicable in most cases.

**Deep learning-based approaches:** With the growing interest in applying deep learning to the medical field [40–43], photoplethysmography (PPG) has emerged as one of its promising applications [44–46] with real-time application [47–51]. One of the most challenging problems in noncontact-based PPG signal estimation is motion artifacts. A slight variation in motion can lead to large variations in output, resulting in unreliable observations. In general, deep learning-based methods follow the steps shown in Figure 10 to measure oxygen saturation levels.

**Temporal convolution:** In the work of Mathew et al. [21], the authors incorporate the basic idea of temporal convolution. The human skin ROI is considered the ROI, and to obtain the PPG signal, this ROI is divided into three color channels (R, G, and B), and the spatial average of these channels is used as the PPG signal. They have cleverly used several channel mixing techniques as defined in Equation (8).

$$V = \sigma(WU + bI^T) \quad (8)$$

After that, 1D convolution with max pooling is performed to extract important temporal features. The output of the last layer is a single value that denotes the oxygen saturation value. For training reference, a commercial pulse oximeter's readings are used to train the data. Experimental value shows that their 3rd

model having alternative channel mixing and convolution-pooling outperforms the other two having the lowest errors for the test dataset. But still, this model is not immune to subject motion, and a slight change in angle can give a larger deviation.

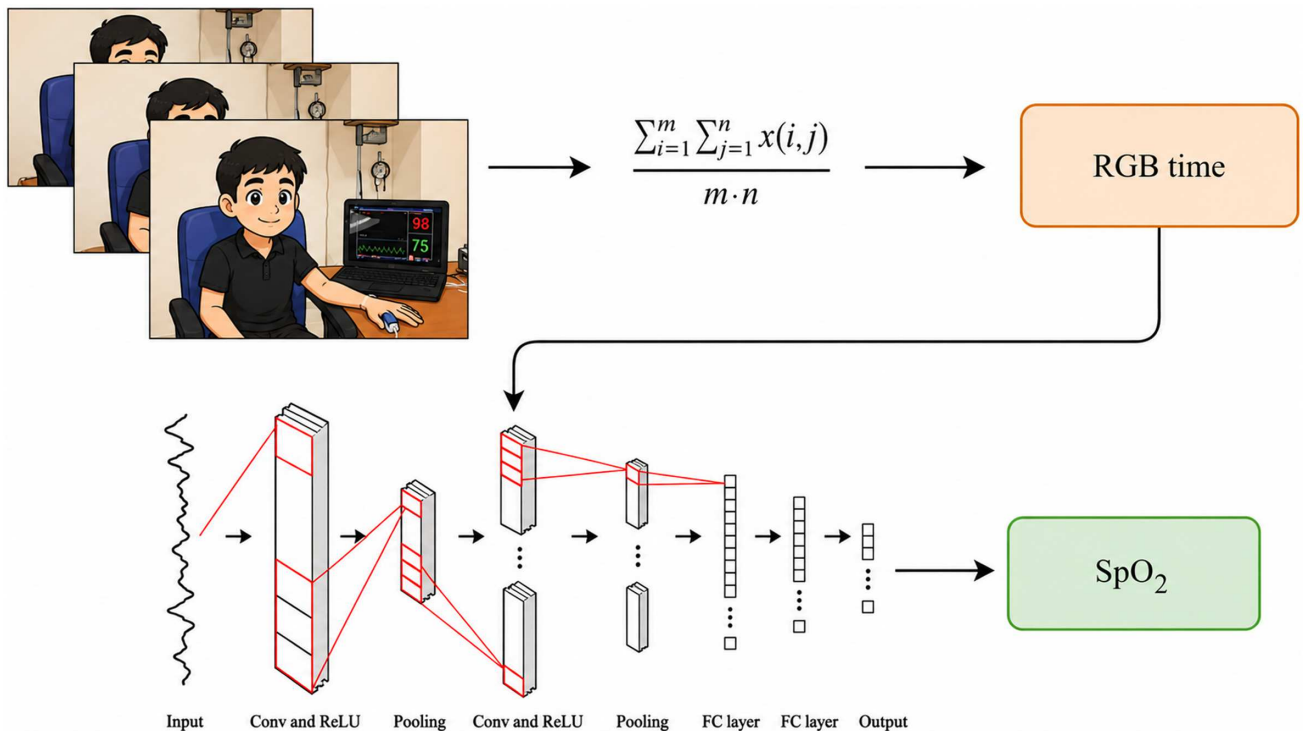
**Wavelength-spectral absorption:** [52] proposed a new method using 12-wavelength spectral absorption measurements to improve accuracy. They have used a 1D convolutional neural network (CNN) model to estimate  $\text{SpO}_2$ . Their analysis shows that it is very important to construct an effective 1D-CNN model area for spectral measurement using the appropriate spectral region and number of wavelengths. Table 10 lists the objectives, strengths, and weaknesses of noncontact deep-learning-based methods to measure blood oxygen saturation. One of the main limitations is calibration, which is countered with the implementation of deep learning algorithms. This table discusses those methods. In Table 11, datasets, accuracy metrics, and accuracy values are listed for noncontact deep learning methods.

**Transformer-based approach:** Chu et al. [53] proposed a transformer-based approach to extract the PPG signal for estimating systolic blood pressure and oxygen saturation.

**Spatial-temporal representation learning:** Cheng et al. [54] used an RGB camera to record video, and a CNN-based model was used to estimate representations from the recorded video data. That representation was finally used to estimate oxygen saturation.

**Other deep learning-based approaches:** Lampier et al. [55] used fingertip videos for estimating blood oxygen saturation using deep neural networks (DNNs). Sharma et al. [56] used a deep learning model to detect sleep apnea using oxygen saturation. Najim et al. [57] used Internet of Things (IoT) and Wireless Sensor Networks (WSN)-based health monitoring systems, where they have used artificial neural networks (ANNs) for the estimation. Mortazavi et al. [58] designed a child-friendly approach for diagnosing apnea. Their method used an Recurrent

Figure 10  
A general architecture for deep learning-based models



**Table 10**  
**Qualitative analysis of methods based on deep learning**

| Method | Objective                                                  | Strength                                                                                      | Weakness                                          |
|--------|------------------------------------------------------------|-----------------------------------------------------------------------------------------------|---------------------------------------------------|
| [21]   | Channel mixing and 1D temporal convolution                 | Manual calibration is removed                                                                 | Sensitive to motion artifact                      |
| [52]   | Multispectral region analysis                              | Improve accuracy, remove motion artifacts, fix low pulse amplitude, and reduce response delay | The complexity of model design                    |
| [53]   | Transformer-based time-series modeling                     | Improved accuracy                                                                             | Not immune to data bias                           |
| [54]   | CNN-based model for representation learning                | Outperforms the conventional ratio-of-ratios-based approach                                   | Not immune to skin-tone bias                      |
| [55]   | Used fingertip video for oxygen saturation measurement     | Cover a wide range of SpO <sub>2</sub> with high correlation                                  | –                                                 |
| [56]   | Detection of sleep apnea                                   | Sensitive to various apnea subtypes                                                           | Oximeter dependent                                |
| [57]   | An IoT and WSN-based framework for monitoring              | High accuracy                                                                                 | –                                                 |
| [58]   | Diagnosing apnea                                           | Child friendly                                                                                | –                                                 |
| [59]   | To reduce computational complexity                         | Reliable and cost-effective                                                                   | Data-size limitation                              |
| [60]   | High-resolution apnea detection                            | Effective and fast                                                                            | –                                                 |
| [61]   | Pulse oximetry-based Apnea-Hypopnea Index (AHI) estimation | –                                                                                             | –                                                 |
| [62]   | Accurate AHI estimation                                    | Reliable and fast                                                                             | –                                                 |
| [63]   | Real-time athlete health monitoring                        | Can diagnose a dreadful disease common in athletes                                            | Sensitive to the number of neurons                |
| [64]   | Contactless SpO <sub>2</sub> monitoring system             | High usability                                                                                | –                                                 |
| [65]   | Hypoxemia event early prediction                           | Enables earlier intervention                                                                  | Trained and tested only on older and ill patients |
| [66]   | Multimodal sleep apnea detection                           | Multimodal                                                                                    | Limited dataset size for training the model       |
| [67]   | Contactless SpO <sub>2</sub> estimation enhancement        | Multi-model fusion                                                                            | –                                                 |
| [68]   | LSTM-based SpO <sub>2</sub> estimation                     | LSTM model for sequence analysis                                                              | –                                                 |
| [69]   | SmartPatch-based SpO <sub>2</sub> prediction               | Real-time casualty monitoring                                                                 | –                                                 |
| [70]   | SmartPatch-based SpO <sub>2</sub> prediction               | Portable, noninvasive system with low prediction error                                        | Small dataset and limited testing                 |
| [71]   | Accurate, robust noncontact SpO <sub>2</sub>               | Accurate and fast                                                                             | Limited data diversity                            |
| [72]   | Noncontact SpO <sub>2</sub> estimation via rPPG            | Low cost, fast, and reliable                                                                  | Limited SpO <sub>2</sub> range                    |
| [73]   | Noninvasive glucose monitoring system                      | The model works on the NIR spectrum                                                           | Limited dataset                                   |
| [74]   | PPG-based Electrocardiogram (ECG) parameter estimation     | Affordable real-time monitoring                                                               | –                                                 |
| [75]   | Habitual activity-based SpO <sub>2</sub> estimation        | Superior performance                                                                          | –                                                 |
| [76]   | Motion artifact-resistant SpO <sub>2</sub> monitoring      | Lower error rate than commercial devices                                                      | –                                                 |

Neural Network (RNN) and a CNN-BiGRU with attention. Shuzan et al. [59] designed a machine learning-based model using Gaussian process regression for oxygen saturation estimation. [60] proposed a 1D convolutional network for detecting apnea. [61] developed a deep learning-based model for sleep stages and respiratory events scoring. [62] introduced a deep learning-based model, OxiNet, for estimating the apnea-hypopnea index from oxygen saturation measurements. [63] designed a deep learning-based IoT-enabled health monitoring system that could track an athlete's vital health signals for better tracking. [64] used smartphone cameras to capture facial video. Then, using support vector machine-based algorithms, they proposed a model for HR estimation. [65] proposed a model named SWIFT (SpO<sub>2</sub>

Waveform ICU Forecasting Technique), which is a deep learning model. This model predicts blood oxygen saturation 5–10 min earlier by analyzing prior oxygen saturation values. [66] proposed an Long Short-Term Memory (LSTM)-based model for sleep apnea detection using blood oxygen saturation and pulse value. Their model achieved high accuracy on sequential data. [67] developed a multi-model fusion mechanism for oxygen saturation measurement from facial video. Their framework integrates a residual and coordinate attention network, a color channel model, and a network-based model for measuring oxygen saturation. [68] designed an LSTM model as an alternative to conventional pulse oximeters. Their proposed two-layer LSTM-based architecture could estimate blood oxygen saturation with high accuracy.

**Table 11**  
**Quantitative analysis of methods based on deep learning**

| Methods | Datasets                                                                              | Metrics used for accuracy measurement    | Result                                                            |
|---------|---------------------------------------------------------------------------------------|------------------------------------------|-------------------------------------------------------------------|
| [21]    | Self-collected video dataset of six males and eight females between the ages of 21–30 | Correlation, MAE, RMSE                   | 0.39(1), 0.41, 0.41<br>2.16(2), 1.96, 1.81<br>2.70(3), 1.48, 2.43 |
| [52]    | –                                                                                     | Correlation (r2)                         | 0.97                                                              |
| [53]    | MIMIC                                                                                 | MAE                                      | 0.56                                                              |
| [54]    | VIPL-HR                                                                               | MAE, RMSE                                | 1.274, 1.71                                                       |
| [55]    | Self-collected dataset                                                                | MAE, RMSE                                | 1.97, 2.92                                                        |
| [56]    | SHHS                                                                                  | Positive predictive value                | 34.2, 41.5                                                        |
| [57]    | –                                                                                     | Mean Absolute Percentage Error (MAPE)    | 1.05                                                              |
| [58]    | CHAT                                                                                  | Kappa                                    | 0.57, 0.63                                                        |
| [59]    | BIDMC                                                                                 | RMSE, MAE                                | 0.98, 0.57                                                        |
| [60]    | UCD St. Vincent's University Hospital's sleep apnea database                          | Sparsity, accuracy                       | 80, 89.75                                                         |
| [61]    | Dataset from Princess Alexandra Hospital                                              | Interclass correlation coefficient (ICC) | 0.946                                                             |
| [62]    | SHHS, CFS, MROS, MESA                                                                 | ICC                                      | 0.96                                                              |
| [64]    | Self-collected dataset                                                                | RMSE, MAE                                | 1.45, 0.92                                                        |
| [65]    | JH-CROWN                                                                              | MSE                                      | 0.0007                                                            |
| [66]    | Sleep Study Unit of the Sismanoglio-Amalia Fleming General Hospital                   | Accuracy                                 | 80.76                                                             |
| [67]    | PURE, VIPL-HR                                                                         | MAE                                      | < 2                                                               |
| [68]    | –                                                                                     | MAE, RMSE                                | 1.68, 2.45                                                        |
| [69]    | BIDMC PPG and Respiration Dataset                                                     | MAE, MSE, RMSE, RMSLE                    | 1.45, 3.85, 1.96, 0.02                                            |
| [70]    | Red, Infrared, Composite (Red + Infrared), Modified Composite                         | MAE, RMSE                                | 1.45, 1.96                                                        |
| [71]    | Self-collected dataset                                                                | MAE                                      | 0.46                                                              |
| [72]    | PURE, ARPOS                                                                           | MAE, RMSE                                | 0.77, 0.96                                                        |
| [73]    | Self-collected dataset                                                                | RMSE                                     | 6.62                                                              |
| [75]    | COHFACE, Olivetti Face                                                                | Jaccard index, accuracy, precision       | 95.92, 97.19, 98.40                                               |

[69] developed a SmartPatch-based SpO<sub>2</sub> monitoring system for emergency triage scenarios, using an embedded PPG sensor. They used a random forest for their regression task. [70] proposed a multiple regression-based model with seven extracted features for monitoring SpO<sub>2</sub>. [71] proposed multispectral SpO<sub>2</sub> prediction model using an LSTM-based encoder. Their model achieves very high accuracy. [72] proposed ROSE-Net that used a PPG video stream as a low-cost alternative to traditional sensor-based models. [73] designed a lightweight CNN and LSTM-based model that works on data of the NIR spectrum. They have used 810, 860, and 940 nm frequencies for their model design. [74] used statistical analysis and predictive modeling including ANN, linear regression, and random forest. [75] extracted facial statistical features such as mean, SD, and entropy to train their supervised model for their estimation. [76] presented the Tactile Intelligence enabled Pulse Oximeter by combining a flexible iontronic interface sensor with a micro-PPG module for accurate SpO<sub>2</sub> monitoring. An encoder–decoder model was designed to process the PPG data to reduce motion artifacts.

**Limitations of deep learning-based approaches:** Although deep learning largely relies on calibration, as it lacks an empirical formula, these methods still have some limitations.

- 1) To train the model to overcome overfitting, a large amount of data is needed along with the true values. This large number of clinical values is difficult to obtain.
- 2) Moreover, many substances in the blood, both indigenous and exogenous, can interfere optically with the right ray even when controlling for the contributions of the static components of arterial blood. This interference generally takes the form of a false absorber or components, besides reduced Hb and O<sub>2</sub>Hb, which absorb light in the red and near-IR wavelengths.

**Summary:** The limitations due to contact were addressed through noncontact-based methods, and deployable models were developed to tackle critical situations involving burn patients, infants, and hypersensitive skin. Noncontact-based methods mainly use ambient light to illuminate the subject and use a camera to capture the signal. The signal is further processed using both ROR and deep learning methods. In the case of ROR methods, because light wavelengths are constrained to the visible range, the IR range cannot be used; hence, to simulate the red–IR combination, the R and G channels are mainly used to measure ROR. This requires calibration, and that limitation has been solved by deploying deep learning methods. In deep learning-based techniques, the

three-color channel's ROIs are averaged to create corresponding time signals, which are then fed into 1D convolutional networks; the last layer predicts the oxygen level. The calculated loss is then back-propagated through the network.

## 8. Discussion

Based on studies, contact-based methods yield more accurate and reliable results, with a lower error rate. Even the reference values used in noncontact-based methods are obtained from devices that primarily use contact-based methods. But as this method generally requires a finger clip, it may cause significant discomfort or render it unsuitable for application. Moreover, calibration in this method is not always a good generalization, as it depends on the sample chosen. However, due to its controlled, specific wavelength, it achieves higher accuracy. Noncontact-based methods are more "user-friendly" in nature as they do not require any clip and can be implemented via mobile devices; they have the potential to gain more popularity. The issue is that these methods use ambient light, which has a mixed spectrum; therefore, more precise signals cannot be obtained. Transmission-based methods offer greater advantages than reflectance methods, as the signal intensity is higher after transmission through the subject's presence, providing a more precise measurement. In general, the reflectance methods produce signals that are about 10 times weaker, making them difficult to calculate.

In the case of noncontact methods, many researchers have adopted different approaches to selecting wavelengths for subject illumination. In reference [37], the authors observed that 611 nm and 880 nm wavelengths perform better if minimizing SNR is considered. Red and blue channels were used in most video-based PPG signaling cases, but it has been shown that the red-green combination provides greater accuracy and reliability. For noncontact-based methods with no direct methods for calculating AC and DC components, the mean was used as the DC component, and the SD as the AC component. Ratio-based noncontact methods rely on the same calibration techniques as contact-based methods. As in this case, the amplitude range is relatively narrow, making it much harder to simulate this ratio-based calculation. Moreover, noncontact methods are highly susceptible to motion artifacts. Due to the relatively large distance between the subject and the sensor, motion introduces instability in the signal. Deep learning-based models do not require calibration and are free from sample dependence, but they require a large dataset that is not fully explored in this segment. But, for a limited dataset, as shown by the researchers, their accuracy is comparable to that of a market-available pulse oximeter. It has been observed that time-series analysis of the PPG signal provides reliable, stable results for measuring blood oxygen saturation.

## 9. New Challenges

With the advent of modern technologies [77–80], blood oxygen saturation via contact and noncontact-based methods has attained a new milestone. The design and the performance of modern-day pulse oximetry are quite reliable, but still, some limitations and challenges are as follows:

- 1) Although the healthy range for oxygen saturation in the case of adults is 95% and above, in the case of infants and premature newborn babies, the range varies a lot. Recent studies show that, for premature babies, the safe range is 88–93%, and after 36 weeks, it is 93%. Studies show that lower saturation

than this is associated with lower weight gain and pulmonary hypertension. Hence, accurate oxygen saturation measurement in infants is vital for their treatment. However, in most studies, the measurement methods focus mainly on adults with a high perfusion range. An accurate and robust method for measuring oxygen in newborn babies can be game-changing.

- 2) In general, babies are born with a healthy heart condition. But recent studies show that 1 in 100 babies is born with a congenital heart defect (CHD). And 25% of them are expected to have critical CHDs (CCHD). Babies with CCHD have lower oxygen saturation and require surgery. In this critical case, correct oxygen measurement can help with better medication, resulting in healthier infants.
- 3) It has been observed that limited research has been conducted using a deep learning architecture. DNNs are outperforming almost every conventional method nowadays with proper datasets and clever tuning. So, this can be a new challenge to solve this problem by using DNNs.
- 4) Moreover, as DNN doesn't have any empirical equation to calibrate, it will be free from any bias regarding the sample choice. The choice of wavelengths remains unclear, as different approaches take different advantages. This can be solved with extensive studies.
- 5) Another challenge is the low visibility. In camera-based methods, proper visibility is a key consideration. But under normal conditions, visibility might be compromised.
- 6) Moreover, methods give reliable results if the oxygen saturation level is within 70–100%. But in some cases, the saturation level may drop. That can be a good challenge to solve. In contact-based reflective measurement, it has been demonstrated that the reflected signal captured by the sensor is 10 times weaker than that in transmissive measurements. Low signal strength creates computational difficulties. Moreover, this is prone to noise.

The Beer–Lambert model, which is used in most cases, implements the ROR, a linear approximation of the real dataset in the range of 70–100%. Hence, the Beer–Lambert model can't predict oxygen saturation at lower levels and even gives incorrect results near the lower bound. This limitation can be improved by using a different mathematical model.

## 10. Future Directions

The future application of this is very widespread, as most healthcare systems need oxygen saturation data for precise medication. An automated system can be designed to perform this task, saving a lot of time.

- 1) Most of the research has been conducted on video-based datasets, creating time-series data. A good approach is to measure blood oxygen saturation levels from still images; with image processing, we can predict oxygen saturation from them. In sudden critical situations, an image is more easily obtainable than a video, and image-based oxygen prediction systems can be a real improvement.
- 2) Lower oxygen levels create discomfort, as there will be less oxygenated hemoglobin and more deoxygenated hemoglobin. We know that deoxygenated hemoglobin absorbs more red light, and oxygenated hemoglobin absorbs less; research based on this information can also be worth exploring.
- 3) Besides this, as a lower oxygen value creates discomfort, both physical and behavioral, there is also a scope of research that can identify the relationship between these two. It can be

important information in military operations. The US military was interested in developing a system to measure and monitor its soldiers' physiological status and global positioning in real time. But till now, to the best of our knowledge, no such system has been designed to solve this problem. With proper use of instrumentation and technology, this can be easily done.

- 4) Most of the researchers choose to maximize the SNR in the case of ROI selection. However, it has been observed that although a higher SNR yields better accuracy, it is less stable in the presence of data fluctuations. Instead, a medium SNR can compensate for both accuracy and stability. So, finding the optimal SNR for this purpose is a promising direction in this field.
- 5) In the contact-based section, both transmitted and reflected subdivisions have some confusion regarding choosing the wavelength. This can be further analyzed to determine the best wavelength combination.
- 6) Large-scale trials on humans and subsequent clinical validation can be further investigated to study the effect in a real-life scenario.

In noncontact-based methods, mostly the R and B channels of the video frames are used as the two wavelengths of the spectrum. However, one group of researchers has shown that, rather than R and B, the R and G combination yields better and more robust results. This can be worth exploring the correct combination of channels to generate PPG signals.

## 11. Conclusion

In this paper, we have presented a survey on blood oxygen saturation level measurement. We have categorized the methods into contact-based and noncontact-based methods based on working principles. Furthermore, the contact-based methods are divided into subcategories, namely, transmittance type and reflectance type, while the noncontact-based methods are divided into subcategories, namely, ratio-based approaches and deep learning-based approaches. For each category, the proposed survey analyses are based on both qualitative and quantitative results. Based on the analysis, we have listed new challenges, applications, and directions. The conclusions based on the analysis may clarify confusion about the methods, measures, ideas, and the strengths and weaknesses of the models. In addition, this survey can help readers gain an overview of state-of-the-art methods and provide a clear idea of directions for future advancement and applications.

## Ethical Statement

The authors declare that this study did not require formal ethical approval or informed consent because the research was conducted entirely using publicly available standard datasets, including VIPL-HR, UBFC-rPPG, COHFACE, and the rPPG-Toolbox resources. The study did not involve direct recruitment of participants, human intervention, or collection of identifiable personal data by the authors. All datasets used in this work were obtained from publicly accessible research repositories and were used in accordance with their respective usage policies and research guidelines.

## Conflicts of Interest

Palaiahnakote Shivakumara is the Editor-in-Chief and Umapada Pal is an Advisory Board Member for *Artificial Intelligence*

and Applications, and they were not involved in the editorial review or the decision to publish this article. The authors declare that they have no conflicts of interest in this work.

## Data Availability Statement

The data that support the findings of this study are openly available in VIPL at [https://vipl.ict.ac.cn/en/resources/databases/201811/t20181129\\_32716.html](https://vipl.ict.ac.cn/en/resources/databases/201811/t20181129_32716.html), in ImViA at <https://sites.google.com/view/ybenzeth/ubfcrppg>, in idiap at <https://publications.idiap.ch/index.php/publications/show/3688>, in GitHub at <https://github.com/ubicomplab/rPPG-Toolbox>, and in arXiv at <https://arxiv.org/pdf/2602.23771>.

## Author Contribution Statement

**Rakesh Dey:** Conceptualization, Methodology, Investigation, Writing – original draft, Visualization. **Shivakumara Palaiahnakote:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Visualization, Supervision. **Umapada Pal:** Writing – review & editing, Supervision. **Sukalpa Chanda:** Validation. **Yue Lu:** Validation.

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