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Original Article

Comparative Analysis of Anatomical Regions for Noninvasive Blood Testing Using Spectroscopic Technique

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Abstract *- Traditional blood collection methods face numerous challenges, including discomfort, the risk of infection, needle injuries, time-consuming procedures, preserving sample integrity, patient non-compliance, the need for specialized training, and logistical complexities. The goal of advancements in blood collection techniques is to make the process less invasive, more comfortable, and more efficient. Spectroscopic techniques are used to study the impact of light on living tissues, providing valuable insights into biological systems and the analysis of haematological profiles. This approach simplifies the process of identifying risk factors for diseases, intervening in a timely manner, and making lifestyle adjustments to prevent or manage chronic illnesses. A collaborative study with Dr. Murugan MBBS, DCH, a specialist in paediatric medicine, has identified the optimal anatomical locations for data collection using spectroscopy. The study utilized spectroscopy to identify the optimal anatomical sites for data collection, including the ear lobe, elbow, wrist, and fingertip. The elbow location demonstrated outstanding performance, effectively avoiding errors and optimizing correlation. The data collected from the elbow will be given priority for further analysis in relation to haematological profiles. The elbow site is highly effective compared to other locations, emphasizing the importance of spectroscopic contact in identifying risk factors for diseases and facilitating timely intervention and lifestyle changes.*

Keywords *- Anatomical location identification, Deep learning algorithms, Haematological Profile, Medical Innovation, Noninvasive technique, Spectroscopic contact.*

1. Introduction

Blood tests are essential for diagnosing and monitoring many health markers [1]. The tests measure blood cell counts, glucose, cholesterol, liver, kidney, thyroid, electrolyte, disease-specific markers, hormone levels, and cancer indicators. The choice of a blood test depends on symptoms, medical history, and medical advice. More blood tests can monitor health markers and identify medical diseases [2]. Medically called a blood draw or venipuncture.

Patient preparation, material procurement, vein identification and selection, tourniquet application, needle insertion, blood sample collection, labelling and processing, and post-operation care are all part of the method [3]. The surgery is usually quick, and the patient is told to keep the arm straight to aid clotting. This method can cause anxiety, particularly in paediatrics. This may lead to challenges like inflammation, infection, vein identification, and risk of injuries. Haematology uses spectroscopy to examine the haematological profile [4]. These methods include haemoglobin concentration, oxygen saturation, blood gas analysis, component differentiation, haematological illness diagnosis, blood coagulation monitoring, flow cytometry, point-of-care testing, and new research. Spectroscopy helps diagnose and monitor blood disorders by measuring blood parameters precisely and non-invasively. Researchers are constantly developing these methods for accuracy and clinical value.

Noninvasive spectroscopic techniques in haematology offer several benefits, including infection reduction, enhanced patient comfort, and real-time monitoring for critical care. They alleviate distress in paediatric patients, conserve resources, enhance data dependability, and expedite examinations. Progress in noninvasive spectroscopy can also facilitate remote monitoring for patients residing in rural or underserved areas [5]. These strategies uphold healthcare ethics and are essential for contemporary healthcare.

2. State of Art

Medical and dental sciences are prioritizing disease prevention through digital technologies, particularly optical technology, which offers rapid, non-intrusive, molecularly specific, on-site analysis of biological tissues [6-9]. Optical biopsy techniques and noninvasive examinations of bodily fluids and tissues using optical technologies hold significant promise for medicine and dentistry [10]. These techniques yield equivalent diagnostic outcomes and patient benefits, but potential risks like delayed histology reports can impact patient prognosis [11].

In recent times, investigations into biofluids have produced promising results. It has been noticed that human blood, saliva, and urine possess significant biochemical potential for diagnostic applications. The utilization of bodily biofluids in spectroscopic procedures is shown to be comparatively more straightforward and efficacious when compared to alternative methods of examination [12]. Miller and Dumas (2006) [13] suggest that the mid-infrared energy range reveals sample molecular compositions and concentrations. Kinetic spectrum analysis has advanced over the past 20 years due to biochemical data from samples' vibrational frequencies [14]. Fourier-transform infrared spectroscopy quantifies light transmission or reflection spectrum intensity reduction due to sample interaction [15].

FT-IR signals can be used in various sampling models, including propagation, attenuated total reflection, and external reflection [16]. Transmission mode applications require sample thickness for IR light transmission, but aqueous materials have a strong affinity for detecting it [17]. FT-IR is a valuable tool in medicinal biology for identifying bacteria, describing neoplastic alterations, and detecting chemical changes from diseases [18]. Its chemical specificity and simple, reproducible, and non-destructive nature make it a potent research tool, with its noninvasive biofluid analysis being a clinical advantage [19, 20]. Spectroscopic diagnostics are more cost-effective than conventional diagnostic methods in sensitivity and specificity scenarios, according to Grey et al. [21]. Thus, widespread usage of the technology may drive doctors to learn more about FT-IR and its uses in disease diagnosis, monitoring, and evaluation. Due to increased demand, the method may favour cost decrease over time.

FT-IR spectroscopy is ideal for real-time chemical investigation of transparent and semi-transparent biofluids due to their transparency and minimal visible light absorption. Other visual spectroscopy methods are less sensitive to biomarkers or require larger sample volumes, making FT-IR the preferred choice for real-time molecular characterization [22]. Complete biofluid samples can be investigated using FT-IR spectroscopy since it can detect chemical biomarkers in small amounts of transparent and semi-transparent materials. Clinical translation relies on analyzing whole biofluid samples (without sample processing) because processing samples would require more clinician training, cost more, and require more instruments (e.g., centrifuges) and/or chemicals (e.g., contrast agents) [23]. FT-IR background signals are affected by optical processes such as light absorption and scattering [24]. Thus, to eliminate optical processes irrelevant to molecular characterization in each application, data processing must be standardized for biofluid analysis. Examine translucent biofluids to reduce light scattering [25].

Additionally, in light of the most recent pandemic, COVID-19, Zhang et al. [26] showed that the FT-IR approach can also be useful for identifying viral infections. The technique's ability to integrate FT-IR with infrared array detector imaging makes it one of the most powerful tools for biochemical and spatial exploration [27, 28]. FT-IR spectroscopic signals may be employed in a variety of sampling modes, such as transmission, attenuated total reflection, and external reflection. Early FT-IR applications employed transmission mode, which requires a thin sample that permits IR light to flow through it [29]. Aqueous samples have a high IR light sensitivity, making transmission mode dissolution investigations more complicated. FT-IR spectroscopy and imaging are effective tools for analyzing structural changes in biological materials such as tissues, cells, and organelles [30]. This article focuses on the application of FT-IR for blood samples.

3. Problem Statement

The drawbacks of conventional blood collection methods are numerous. Patients often experience pain and discomfort while also facing an increased risk of infection. Complications such as bruising or inflammation can arise, and accessing veins can be challenging. Healthcare workers are also at risk of needle stick injuries. Additionally, these methods are time-consuming and may affect sample quality due to haemolysis. Patient non-compliance can be a result, and specialized training is required. However, scientists are currently focused on creating new approaches and advanced technology for blood collection to tackle these difficulties. These advancements aim to make the treatment less invasive, more comfortable, and more efficient. These innovative methods strive to improve the overall patient experience and ensure their safety by reducing pain and anxiety, improving sterilization techniques, and minimizing complications.

Furthermore, the incorporation of advanced technology like vein finders and devices for blood collection from alternate sites, such as capillary blood sampling, can effectively tackle the difficulties related to accessing veins. Scientists are currently studying noninvasive or less invasive techniques, like spectroscopic diagnostics, to eliminate the need for venipuncture. These advancements improve patient comfort and reduce the risk of needle stick injuries for healthcare professionals. In addition, the use of automated blood collection devices and point-of-care testing systems can streamline the process, leading to savings in time and resources. In addition, these innovations aim to improve sample quality by minimizing haemolysis and ensuring accurate test results. These advancements could revolutionize the industry by addressing the limitations of conventional blood collection techniques, leading to improved safety, efficiency, and accessibility for patients and healthcare professionals.

4. Proposed Methodology

Acquiring physiological data from different parts of the body can provide valuable insights, depending on the type of data being collected. The ear lobe is often used as a site for collecting capillary blood samples to measure glucose levels and oxygen saturation. In addition, it can be used to measure temperature and evaluate peripheral perfusion. The antecubital fossa, situated in the elbow, is a prime location for acquiring venous blood samples for comprehensive blood tests and for evaluating blood pressure.

In addition, it is commonly used for intravenous access. Wearable devices placed on the wrist are utilized to measure a range of physiological parameters, including pulse rate, heart rate variability, activity levels, movement patterns, skin temperature, and electrodermal activity. Finally, the fingertip is often used to collect capillary blood samples, measure oxygen saturation, monitor pulse rate, and evaluate skin temperature.

Each anatomical location provides unique advantages for gathering different types of physiological data. The ear lobe is a suitable location for efficient capillary blood testing and continuous monitoring of oxygen saturation, offering a less invasive and more appropriate option. The elbow is an ideal location for collecting larger amounts of blood and for obtaining accurate blood pressure measurements. Wearable technology enables the ongoing monitoring of heart rate, activity levels, and stress, making the wrist an ideal spot for these measurements.

The fingertip is an efficient site for collecting capillary blood samples and measuring pulse oximetry. It is a straightforward process that requires minimal effort. The choice of the venue depends on the specific requirements of the study or clinical evaluation, as well as the balance between data accuracy, patient satisfaction, and practicality. This study aims to determine the optimal anatomical locations for data collection using spectroscopic techniques, considering various factors.

4.1. Experimental Setup

The experimental setup of the current research is shown in Figure 1. A total of 45 Participants in the control group aged between 3 to 12 years are involved in this study. Using spectroscopy with wavelengths ranging from 191 nm to 1118 nm, measurements have been made from four unique anatomical regions: (1) the ear lobe, (2) the elbow, (3) the wrist, and (4) the fingertip for the participant's characteristics shown in Table 1.

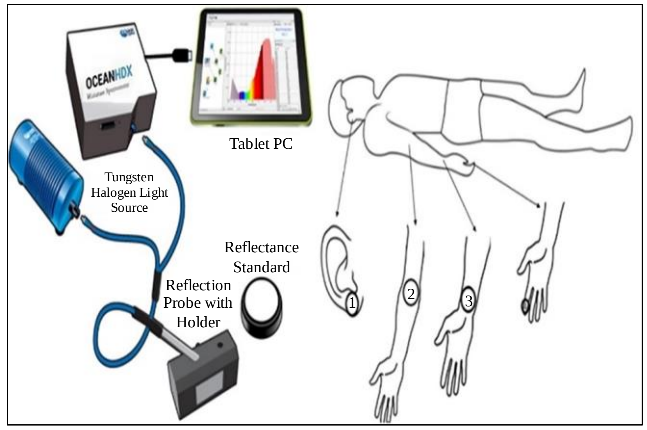

Fig. 1 Experimental setup for spectroscopic examination

Table 1. Participant's characteristics

Parameters	Children's	Adults
Height	115.12±14.01	151.00±7.90
Weight	19.64±6.07	40.90±7.83
Age	7.00±5.00	14.00±2.00
Gender	Male: 20	Male: 05
	Female: 18	Female: 02

4.2. Study Site

Spectroscopy was used to collect the data at NM Hospital, and it was done from four separate anatomical regions: the ear lobe, the elbow, the wrist, and the fingertip. Executed in conjunction with Dr. Murugan, who is a Child Specialist and holds the degrees of MBBS and DCH.

4.3. Method

Reflectance refers to the property of a material or surface to reflect light. The noninvasive probe was positioned on capillaries located at the fingertip, ear lobes, wrist, and elbow to obtain measurements. The experimental setup built in this study consisted of a Reflectance NIR spectrometer, namely the OCEAN HDX model, with a wavelength range of 200-1100 nm.

A Deuterium Halogen light source, specifically the DT 3000 model, was employed to provide the necessary illumination. A reflection probe, denoted as QR 400-7-VIS-NIR, was used to collect the reflected light from the sample. To ensure stability and proper positioning of the probe, a probe holder (RPH-1) was utilized. The measurement setup used in this study is illustrated in Figure 2.

4.4. Measurement Protocol

- The measurements and recording encompassed the anthropometric variables of the individual, namely height, weight, age, and gender.
- The subject was instructed to assume a supine position for approximately five minutes, with strict adherence to immobility of the body and hands.
- Navigate to the Welcome page within the Ocean View 1.6.7 software interface. Proceed to configure the spectroscopic application wizards, and after that, select the reflectance icon to initiate the measurement of reflectance.
- Ensure that the complete signal encompasses the entire range of wavelengths, spanning from 191nm to 1118nm.
- It is recommended to use the Active acquisition option for the acquisition process. Additionally, the acquisition parameters should be set as follows:

  - Integration Time: Automatic
  - Scan to Average: 2 to 3
  - Boxcar width: 10

- A reference spectrum was acquired using the WS-1 Diffuse Reflectance Standard, which is composed of Polytetrafluoroethylene (PTFE), a white plastic material that exhibits diffuse reflectance properties and serves as a Lambertian reference surface for research on reflectance. Next, go to select the icon labelled "Store Reference Spectrum."
- To initiate the process, disable the light source and proceed to record a spectrum with minimal light intensity by selecting the "Store Dark Spectrum" item situated within the toolbar.
- The measurement of blood flow reflectance within the human body involves the targeted application of a predetermined quantity of light across certain anatomical locations, including the elbow, wrist, fingertip, and earlobe. This light encompasses a range of wavelengths running from 191nm to 1118nm.
- The observed total reflectance is expressed as a percentage (%R) in relation to the reflectance of a standard reference substance, as demonstrated in the following equation,

$$\% R_{\lambda} = \frac{S_{\lambda} - D_{\lambda}}{R_{\lambda} - D_{\lambda}} \text{ X } 100 \quad (1)$$

Where,
$S\lambda$= The sample intensity at wavelength λ,
$D\lambda$= The dark intensity at wavelength λ,
$R\lambda$= The reference intensity at wavelength λ.

Gather spectroscopic readings from each anatomical location, including the ear lobe, elbow, wrist, and fingertip, are shown in Figure 2. Document supplementary variables that could potentially impact the spectroscopic measurements. The collected data is analyzed using deep learning methods to identify the most suitable body portion for spectroscopic engagement.

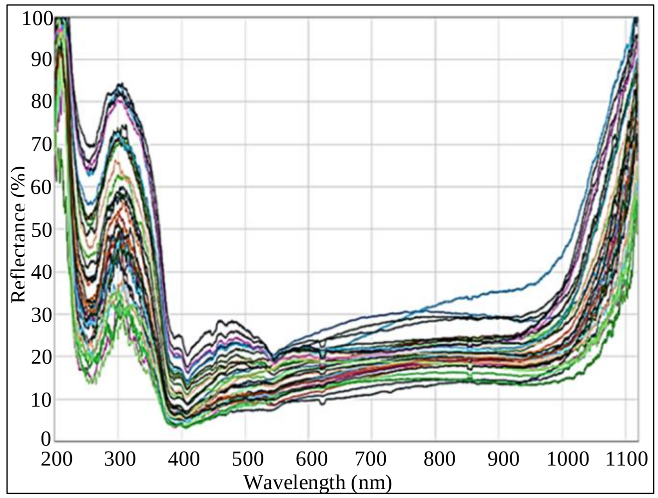

Fig. 2 Reflectance measured from elbow, wrist, fingertip, and earlobe

5. Result and Discussion

The research used data from 45 participants aged 1-15 years, with 27 males and 18 females. The residual sum of squares measures the error rate in polynomial regression or mean squared error. A decrease in mean square error indicates better fit, but higher-degree polynomials can lead to overfitting.

Cross-validation is used to assess model efficacy on unfamiliar data and determine optimal polynomial degrees. The correlation coefficient is used to quantify the linear association between variables. Mean square error and correlation error coefficients are computed for each regression polynomial.

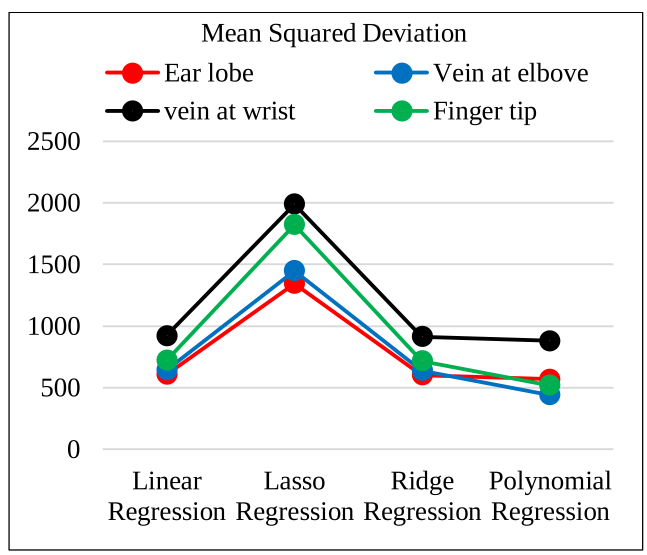

Fig. 3 Comparison of Mean Squared Deviation of algorithms across various anatomical regions

The graph in Figure 3 illustrates a comparison of error rates for different biometric measurement locations using various regression algorithms. The locations include the ear lobe, the vein at the elbow, the vein at the wrist, and the fingertip. The regression techniques used are Linear Regression, Lasso Regression, Ridge Regression, and Polynomial Regression. Polynomial Regression consistently achieves the most accurate results at all measurement locations. On the other hand, Lasso Regression shows the highest error rates across all sites. Typically, the error rates for the vein at the wrist are higher in most regression approaches than in other locations. Polynomial Regression emerges as the most accurate technique for these biometric measures, while Lasso Regression lags behind in terms of precision.

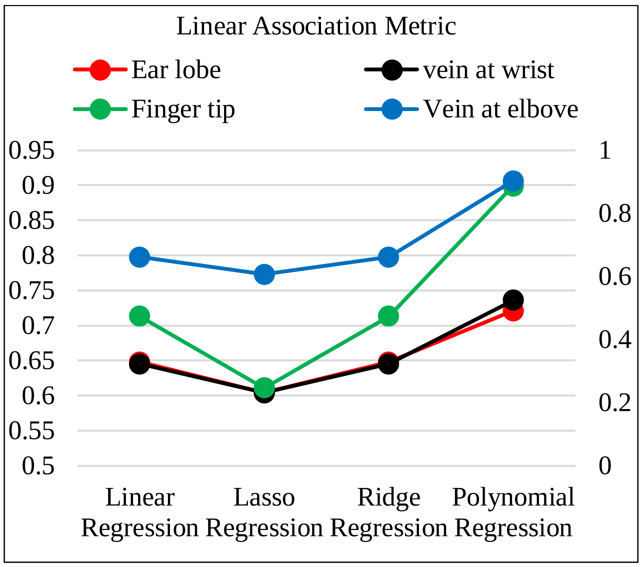

Fig. 4 Comparison of linear association metrics across different anatomical regions for various algorithms

The graph in Figure 4 displays a comparison of correlation coefficients for different biometric measurement locations (Ear lobe, Vein at elbow, Vein at wrist, and Fingertip) using different regression methods (Linear Regression, Lasso Regression, Ridge Regression, and Polynomial Regression). The correlation coefficients measure the level of connection between anticipated and real values.

Polynomial Regression yields highly accurate correlation coefficients across all sites, indicating a strong and reliable relationship between projected and actual values. Lasso Regression reveals the least significant correlation coefficients across all sites, indicating a weaker association. The vein located at the elbow and fingertip shows strong correlation coefficients when using Polynomial Regression, with values of 0.903 and 0.899, respectively. This highlights the effectiveness of capturing these biometric measures. When it comes to correlation, Lasso Regression shows the lowest performance, while Polynomial Regression demonstrates the highest predictive accuracy.

The study uncovers that the elbow region exhibits the lowest error rate and highest correlation, suggesting the possibility of a gender-related factor that could validate this phenomenon.

5.1. Cross-Validation with Gender

The study involved 27 male participants, analyzing data for Haematological analysis. Ethical and privacy issues were addressed with informed consent and anonymization. From Figures 5, 6, 7 and 8, it was examined that the elbow region outperforms with minimum error in Polynomial regression. A total of 18 female participants were involved in the current study. The gathered data is analyzed based on the gender variation and the cumulative results for the female participants, along with the graphical representation of the mean square error and correlation coefficients shown in Figures 7 and 8, respectively.

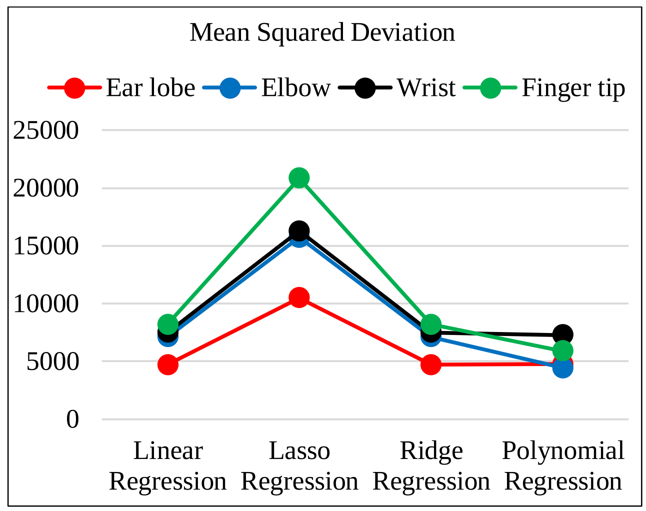

Fig. 5 Comparison of Mean Squared Deviation of algorithms across various anatomical regions for male participants

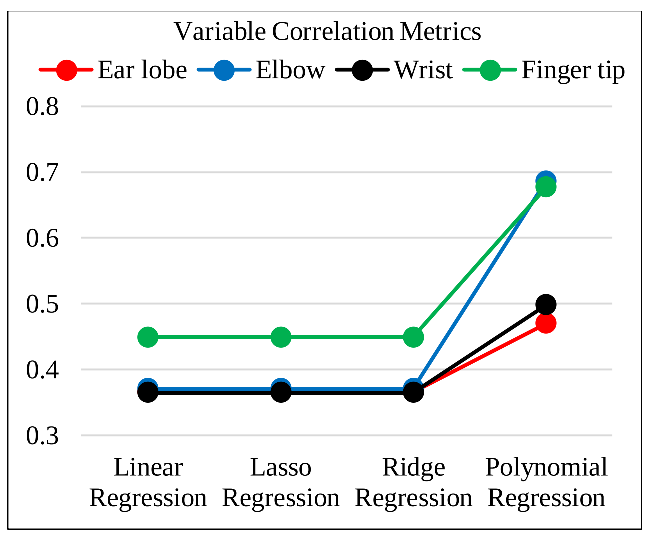

Fig. 6 Comparison of variable correlation metrics across various anatomical regions for different algorithms in male participants

The two graphs in Figures 5 and 6 present valuable information about the performance of different regression methods for various biometric measurement locations. They specifically focused on Mean Square Error (MSE) and correlation coefficients for male participants. The graph in Figure 5 displays the MSE values, revealing that Polynomial Regression consistently produced the lowest MSE for all locations, suggesting a higher level of predictive accuracy.

However, Lasso Regression exhibited the highest Mean Squared Error (MSE) across all locations, suggesting its predictive performance was the weakest. In terms of the ear lobe location, Polynomial Regression achieved the lowest MSE of 4744.41, while Lasso Regression had the highest MSE of 10480.22. When it comes to the elbow location, Polynomial Regression achieved the most favorable Mean Squared Error (MSE) of 4437.04, whereas Lasso Regression yielded the least desirable MSE of 15716.96. When considering the wrist location, it is worth noting that Polynomial Regression achieved the lowest Mean Squared Error (MSE) of 7284.24, indicating its superior performance.

On the other hand, Lasso Regression exhibited the highest MSE of 16291.43, suggesting that it may not be as effective in this context. Finally, in terms of the fingertip location, Polynomial Regression achieved the lowest Mean Squared Error (MSE) with a value of 5898.59. At the same time, Lasso Regression performed the poorest with a Mean Squared Error of 20837.74. The graph in Figure 6 displays the correlation coefficients, revealing that Polynomial Regression achieved the highest correlation coefficients across all locations. This suggests a strong relationship between predicted and actual values.

On the other hand, Lasso Regression demonstrated the lowest correlation coefficients across all locations, suggesting a less strong predictive relationship. In the case of the ear lobe location, the correlation coefficients varied around 0.35. Polynomial Regression consistently proves to be superior to other regression methods in terms of MSE and correlation coefficients, establishing itself as the most dependable method for biometric measurements. Lasso Regression shows the lowest performance in both metrics, suggesting it is not very effective for these biometric predictions. The Elbow and Fingertip locations demonstrate notable enhancements with Polynomial Regression in both graphs, indicating that these sites are more accurately measured using this method.

The two graphs in Figures 7 and 8 offer important details on the performance of different regression methods for various biometric measurement locations. They specifically focus on Mean Square Error (MSE) and correlation coefficients for female participants. Based on the MSE graph, it is evident that Polynomial Regression consistently outperforms other methods in terms of predictive accuracy. This suggests that Polynomial Regression is a reliable choice for accurate predictions in various locations. However, Lasso Regression shows the highest Mean Squared Error (MSE) for all locations, suggesting the lowest predictive performance. Additionally, the provided data includes the MSE values for each location.

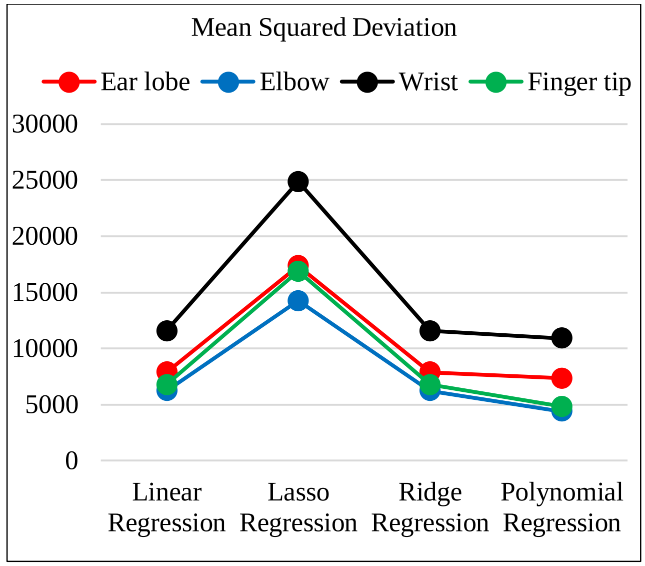

Fig. 7 Graphical representation of the Mean Squared Deviation for female participants

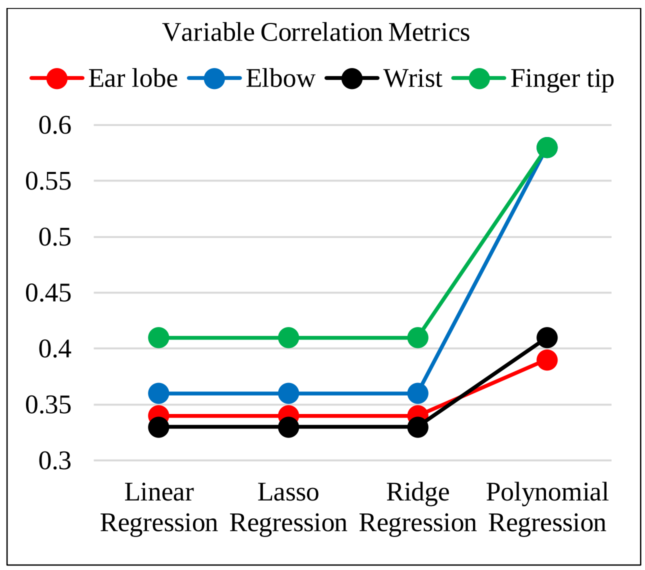

Fig. 8 Comparison of variable correlation metrics across various anatomical regions for different algorithms in female participants

The correlation coefficients graph reveals that Polynomial Regression consistently outperforms other methods in terms of predicting values, suggesting a strong relationship between predicted and actual values. However, Linear, Lasso, and Ridge Regression exhibit comparable and lower correlation coefficients in comparison to Polynomial Regression. Additionally, the provided data includes correlation coefficient values for each location. Based on the analysis of the graphs, it is evident that Polynomial Regression consistently outperforms other regression methods in terms of MSE and correlation coefficients. This makes it the most reliable method for biometric measurements in female participants. However, Lasso Regression demonstrates the weakest performance in both metrics, suggesting it is the least effective for these biometric predictions. In addition, the locations of the elbow and fingertips demonstrate notable enhancements in both Mean Squared Error (MSE) and correlation coefficients when utilizing Polynomial Regression. This underscores the effectiveness of Polynomial Regression for these specific areas. In terms of performance, Polynomial Regression stands out as the top method for female participants. It consistently produces the lowest errors and exhibits the strongest predictive relationships across all biometric measurement locations.

Polynomial Regression consistently emerges as the most accurate method for both male and female participants. It exhibits the lowest Mean Squared Error (MSE) and the highest correlation coefficients across all biometric locations. However, Lasso Regression proves to be the least effective approach for both genders, as it exhibits the highest Mean Squared Error (MSE) and the lowest correlation coefficients. Polynomial Regression proves to be highly effective for determining the locations of the Elbow and Fingertips, highlighting its usefulness in these areas. Based on the aforementioned tables and accompanying graphs, it can be inferred that the elbow region exhibits the highest correlation and the least amount of inaccuracy. This characteristic renders it suitable for investigation within the scope of the present research.

5.2. Statistical Analysis

A statistical analysis has been done to examine the difference among four anatomical sites of the elbow, the ear lobe, the fingertip, and the wrist between two groups of Haemoglobin profiles obtained through the traditional (invasive) and the conventional (noninvasive) methods. The comparative values of p-values, R2, F score and F critical values are shown in Table 2. An ANOVA was used to examine the differences among anatomical sites. The analysis shows the elbow site reveals the most statistically significant findings. The p-values suggest a strong relationship between actual and predicted hemoglobin levels at this site. Furthermore, correlation analysis supports the elbow site has a comparatively better alignment among all tested sites.

Table 2. Comparative statistical analysis by anatomical site

Parameters	p-Value	R^2 Value	F Score	F Critical
Elbow	0.89	0.64	0.01	4.35
Fingertip	0.66	0.58	0.19	4.35
Ear lobe	0.30	0.03	1.12	4.35
Wrist	0.03	0.57	10.64	4.35

6. Conclusion

In this phase, data was collected from four distinct anatomical regions, namely the ear lobe, the elbow, the wrist, and the fingertip, utilizing spectroscopy techniques encompassing wavelengths spanning from 191nm to 1118nm. The data was subsequently subjected to analysis to choose the most suitable body portion for spectroscopic engagement through the utilization of deep learning techniques.

Based on the results of the investigation, it can be concluded that the elbow position exhibits greater performance compared to the other positions, as it demonstrates the lowest error rate and the highest correlation coefficient. Consequently, the data obtained from the elbow will be accorded greater priority in future investigations pertaining to haematological profiles.

Limitation

This study is susceptible to the measurement protocol. One should adhere to the experimental setup. Also, improper setting up of the dark and light reference leads to small variations in reflection percentage in the measurement.

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