


Feasibility of Total White Blood Cells Counts by Visible-Near Infrared Spectroscopy[†]

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[†] Presented at the 1st International Electronic Conference on Chemical Sensors and Analytical Chemistry, 01–15 July 2021; Available online: <https://csac2021.sciforum.net/>.

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Abstract: Total white blood cells (WBC) count is an important indication for infection diagnosis, in both human and veterinary medicine. State-of-the-art WBC counts are performed by flow cytometry combined with light scattering or impedance measurements, in the clinical analysis laboratory. These technologies are complex and difficult to be miniaturized into a portable point-of-care (POC) system. Spectroscopy is one of the most powerful technologies for POC miniaturization due to its capacity to analyze low sample quantities, little to no sample preparation, and 'real-time' results. WBC is in the proportion of 1:1000 to red blood cells (RBC), and the latter dominate visible-near infrared (Vis-NIR) information due to their large quantities and hemoglobin absorbance. WBC are difficult to be detected by traditional spectral analysis because their information is contained within the interference of hemoglobin bands. Herein, we perform a feasibility study for the direct detection of WBC counts in canine blood by Vis-NIR spectroscopy for veterinary applications, benchmarking current chemometrics techniques with self-learning artificial intelligence - a new advanced method for high-accuracy quantification from spectral information. Results show that total WBC counts can be detected by Vis-NIR spectroscopy to an average detection limit of 7.8×10^9 cells/L, with an R^2 of 0.9880 between impedance flow cytometry analysis and spectral quantification. This result opens new possibilities for reagent-less POC technology in infection diagnosis. As WBC counts in dogs range from 5 to 45×10^9 cells/L, the detection limit obtained in this research allows concluding that the combined use of spectroscopy with this SL-AI new algorithm is a step towards the existence of portable and miniaturized Spectral POC hemogram analysis.

Keywords: Point-of-care; Spectroscopy; White blood cells; Artificial Intelligence

Citation: Barroso, T.G.; Ribeiro, L.; Gregório, H.; Santos, F.; Martins, RC Title. *Journal Not Specified* **2021**, *1*, 0. <https://doi.org/>

Received:

Accepted:

Published: 01 July 2021

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1. Introduction

Total white blood cells (WBC) count is one of the most requested hematology parameters because of its broad diagnostic value, including for infection and leukemia. Leukocytosis and leukopenia, which are abnormal values (high/ low, respectively) in WBC counts, are more frequently associated with neutrophil changes, although other leukocytes and neoplastic cells can also cause fluctuations. Neutrophilia is usually related to inflammation, and neutropenia to greater peripheral use or reduced bone marrow production [1].

Most common methods for WBC differential are based on electrical impedance, laser light scattering, radiofrequency conductivity, and/or flow cytometry [2]. The basic principles of operation for automated hematology analyzers are based on cell size affecting directly impedance and scattering angle. This approach has disadvantages for WBC differential, because cell sizes for each type of leukocyte are highly dependent on

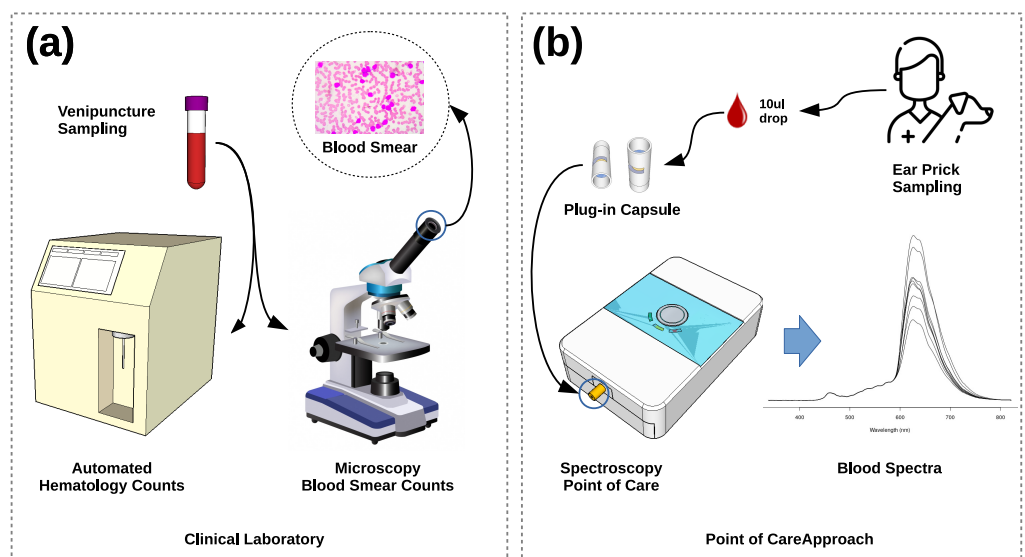


Figure 1. Total white blood cell counts: (a) current laboratory methods - automated cell counting using electric impedance or laser scattering, and manual smear count at the microscope by trained hematologist; and (b) Point-of-care approach - single blood drop spectroscopy counts using artificial intelligence.

35 the development stage and differentiation, leading to inaccurate counts in current auto-
 36 mated equipment [3]. Despite laser scattering technology provides better accuracy than
 37 impedance technology, the latter is widely adopted in Veterinary Medicine. Impedance
 38 counting is a cheaper technology and the best hematology practices recommend that
 39 blood smear microscope counts are performed on abnormal cases [4].

40 Spectroscopy is one of the leading technologies for the development of reagent-
 41 less point-of-care (POC) devices [5,6], capable of providing comprehensive clinical
 42 information from a single drop of blood ($<10\mu\text{l}$), with little or no sample preparation
 43 and real-time results.

44 Visible short-wave near-infrared (Vis-SWNIR) spectroscopy is an information-rich
 45 technology that carries both physical and chemical information, where the information
 46 about blood cells and constituents is distributed across the different wavelengths. Dom-
 47 inant spectral information in blood comes from highly absorbent constituents in the
 48 Vis-SWNIR region, such as hemoglobin present in red blood cells (RBC) and bilirubin in
 49 serum.

50 WBC is present in significantly lower quantities than RBC ($\sim 1:1000$), being con-
 51 siderably more difficult to be detected because the information about WBC is a small
 52 interference effect on the hemoglobin bands. State-of-the-art chemometrics and arti-
 53 ficial intelligence technologies are unable to deal with small-scale interference and
 54 non-dominant spectral information sample constituents with good accuracy [6]. Such
 55 may lead to non-causal correlation in spectroscopy quantification, where the quantifica-
 56 tion is not obtained by direct relationship to the spectral absorbance bands, but rather by
 57 intrinsic correlations of the dataset [7], which may lead to erroneous diagnosis [6].

58 In this research, we study the capacity of WBC quantification by Vis-SWNIR spec-
 59 troscopy and a new algorithm based on Self-Learning Artificial Intelligence [6]. This new
 60 approach isolates spectral interference by searching consistent covariance between WBC
 61 and spectral features - the covariance mode (CovM). CovM is a set of samples that allow
 62 the direct relationship between spectral features and WBC, by sharing the same latent
 63 structure information [6]. Ideally, the relationship between WBC and spectral features is
 64 given by a single eigenvector or latent variable (LV), allowing to unscramble spectral
 65 interference in complex samples such as blood.

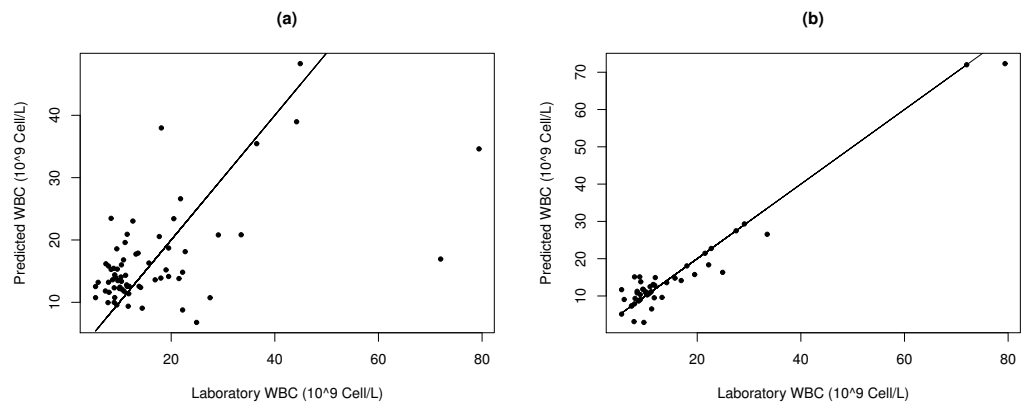


Figure 2. Total white blood cell counts spectral quantification: (a) PLS and (b) SL-AI.

66 Herein, we provide a feasibility study on using Vis-SWNIR spectroscopy for the
 67 quantification and diagnosis of WBC, by providing a benchmark between a common
 68 chemometrics technique - partial least squares (PLS), and our new methodology (SL-AI).

69 2. Materials and Methods

70 2.1. Hemogram analysis

71 Dog blood samples from routine clinical practice were collected by qualified per-
 72 sonnel by standard venipuncture, at the Centro Hospitalar Veterinário do Porto. WBC
 73 was determined by Beckman-Coulter capillary impedance [?] using a Mindray B-2800
 74 vet auto-hematology analyzer.

75 2.2. Spectroscopy

76 Blood spectra were recorded using a POC prototype using a 4500K power LED as
 77 light source, and an USB-based miniaturized spectrometer (Ocean Insight STS-vis) with
 78 an optical configuration and plug-in capsule system according to [5]. LED temperature
 79 and spectrometer integration times were automatically managed to maintain result
 80 consistency. Three replicates measurements were made for each blood sample.

81 2.3. Chemometrics

82 Spectral records were subjected to scattering correction (Mie and Rayleigh) before
 83 modeling. A feasibility benchmark is performed between PLS and SL-AI methods. PLS
 84 maximizes the global covariance between spectral features and WBC, by determining
 85 the orthogonal eigenvectors of the covariance matrix. The relationship between WBC
 86 and signal features is derived by the latent variables (LV), at each deflation. The number
 87 of LV is determined by cross-validation at the minimum value of the predicted residuals
 88 sum of squares (PRESS) [8].

89 SL-AI searches for stable covariance in spectral datasets, finding covariance modes
 90 (CovM). CovM is a group of samples that hold the same interference information char-
 91 acteristics, carrying proportionality between WBC and spectral features. Ideally, the
 92 CovM relationship between WBC and spectral features is given by a single eigenvector
 93 or latent variable (LV). The CovM is validated by leave one-out cross-validation [6].

94 3. Results and Discussion

95 PLS attains a correlation of 0.5687 and a SE of 11.60×10^9 cell/L (Table 1). PLS
 96 analysis demonstrates that there is a significant correlation between spectral features
 97 and WBC, and the small-scale interference of WBC is present in the spectra records.
 98 PLS model is obtained with 5 LV. Such means that the interference information about
 99 WBC in the blood Vis-SWNIR spectra is present in a significant number of differentiated
 100 covariance modes, where the non-dominant spectral interference can be related to WBC.

Table 1. This is a table caption. Tables should be placed in the main text near to the first time they are cited.

Method	SE	LV	R ²	MAPE(%)	R _{Pearson}
PLS	11.06	5	0.3234	44.62	0.5687
SL-AI	2.16	3	0.9473	20.00	0.9733

101 PLS collapses the 5 LV into a single linear coefficient, which relates the WBC to the
 102 recorded spectra, leading to an averaged representation of all covariance modes present
 103 in the dataset. Such results in a high SE and MAPE of 44.62%. The PLS model is unable
 104 to estimate WBC values above 45.00×10^9 cell/L, misdiagnosing severe infection cases
 105 (Figure 2).

106 The minimal total error criteria established by the American Society for Veterinary
 107 Clinical Pathology (ASVCP) for WBC is 20%. PLS shows to be unable to provide the
 108 necessary accuracy for WBC spectral POC technology.

109 SL-AI has a significantly higher correlation ($R=0.9733$), a SE of 2.16×10^9 cell/L,
 110 and a MAPE of 20.00%. SL-AI covariance modes are obtained with 3 LV (Table 1).
 111 Results show that the different covariance modes (CovM) hold spectral interference
 112 proportional to WBC. Such demonstrates that it is possible to search non-dominant
 113 spectral interference from WBC and correlate it to total WBC count.

114 SL-AI CovM relationships are obtained with 3LV. This is an indication that inter-
 115 ference with other constituents and WBC differential population are incorporated in
 116 total WBC count, and that this higher complexity is not completely unscrambled in
 117 the dataset. In ideal conditions, CovM is obtained with a single LV (one eigenvector),
 118 directly relating the constituent concentration to spectral interference. The results show
 119 that non-dominant WBC spectral interference information has high complexity, which
 120 can be attributed to complex immune response, where differentiated cell types act at
 121 different stages and levels of infection or inflammation. The LV number re-assures the
 122 need for further studies, in order to investigate the source of non-dominant spectral
 123 interference attributed to WBC. Results may be improved by:

- 124 i. Larger dataset - more data can help to complement the information of consistent
 125 CovM, allowing detection of single LV CovM;
- 126 ii. Feature space optimization - optimize the search for a feature space that better
 127 discriminates the small variation of WBC interference (e.g. Fourier or Wavelets
 128 decomposition).

129 Despite the limitations shown in this feasibility study, WBC quantification using
 130 Vis-SWNIR spectroscopy in conjunction with the new SL-AI algorithm can attain a total
 131 error estimate of 20%. Such result is following the ASVCP total allowable error for WBC
 132 in dog blood [4], but is above the 15% total allowable error in humans defined by CLIA
 133 [9].

134 4. Conclusions

135 This feasibility study has shown that low intensity, non-dominant, and multi-scale
 136 interferent spectral information is possible to be accessed by unscrambling informa-
 137 tion with the CovM principle included in our SL-AI method. The smaller quantities of
 138 WBC and corresponding interference with dominant constituents such as erythrocytes,
 139 hemoglobin, and bilirubin, are detectable in each CovM. The results allow us to con-
 140 clude that a spectral POC in the Vis-SWNIR for measuring WBC is achievable, for the
 141 application in both veterinary and human medicine.

142 **Author Contributions:** Barroso TG, Ribeiro L, and Gregório H: Investigation, methodology,
 143 validation, writing - review & editing; Santos E: investigation, hardware and firmware; Martins

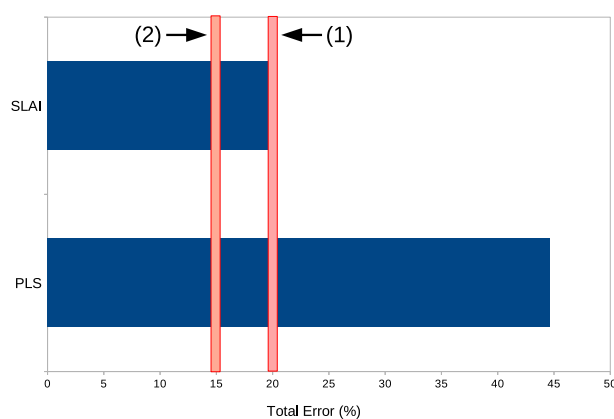


Figure 3. Percentage Total Error for PLS and SL-AI predictions: (1) ASVCP acceptable error limit (20%) and (2) CLIA acceptable error limit (15%)

144 **RC:** conceptualization, software and hardware, funding acquisition, writing - original draft,
 145 resources and formal analysis, project administration.

146 **Funding:** Martins RC acknowledges Fundação para a Ciência e Tecnologia (FCT) research contract
 147 grant (CEEIND/017801/2018).

148 **Conflicts of Interest:** The authors declare that they have no known competing financial interests
 149 or personal relationships that could have appeared to influence the work reported in this paper.

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