Review

Application of Optical Quality Control Technologies in the Dairy Industry: An Overview

Dmitriy E. Burmistrov ¹ , Dmitriy Y. Pavkin ² , Artyom R. Khakimov ² , Dmitry N. Ignatenko ¹,
Evgeniy A. Nikitin ² , Vasily N. Lednev ¹ , Yakov P. Lobachevsky ², Sergey V. Gudkov ^{1,3}
and Andrei V. Zvyagin ^{3,4,5,*}

- ¹ Prokhorov General Physics Institute of the Russian Academy of Sciences, Vavilova Str. 38, 119991 Moscow, Russia; dmitriiburmistroff@gmail.com (D.E.B.); dmitriyek13104@yandex.ru (D.N.I.); lednev@kapella.gpi.ru (V.N.L.); S_makariy@rambler.ru (S.V.G.)
- ² Federal State Budgetary Scientific Institution "Federal Scientific Agroengineering Center VIM", 1st Institutsky Proezd 5, 109428 Moscow, Russia; dimqaqa@mail.ru (D.Y.P.); arty.hv@gmail.com (A.R.K.); evgeniy.nicks@yandex.ru (E.A.N.); lobachevsky@yandex.ru (Y.P.L.)
- ³ The Institute of Biology and Biomedicine, Lobachevsky State University of Nizhni Novgorod, 603950 Nizhni Novgorod, Russia
- ⁴ MQ Photonics Centre, Macquarie University, Sydney 2109, Australia
- ⁵ Center of Biomedical Engineering, Sechenov University, 8 Trubetskaya Str., 119991 Moscow, Russia
- * Correspondence: andrei.zvyagin@mq.edu.au

Abstract: Sustainable development of the agricultural industry, in particular, the production of milk and feed for farm animals, requires accurate, fast, and non-invasive diagnostic tools. Currently, there is a rapid development of a number of analytical methods and approaches that meet these requirements. Infrared spectrometry in the near and mid-IR range is especially widespread. Progress has been made not only in the physical methods of carrying out measurements, but significant advances have also been achieved in the development of mathematical processing of the received signals. This review is devoted to the comparison of modern methods and devices used to control the quality of milk and feed for farm animals.

Keywords: optical diagnostics; analyzer; infrared spectroscopy; analysis of milk; analysis of feed; NIRS; MIRS

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1. Introduction

Milk, as well as food products made from it (cottage cheese, cheese, yoghurts, etc.), are important elements of the human diet [1–3]. As is well known, the volume of consumed dairy products over the past decades has grown significantly [4,5]. In 2015, 497 million metric tons of cow milk was produced worldwide; by 2020, that figure had risen to around 532 million metric tons [6]. The constant increase in the consumption of milk and milk-containing food products requires the improvement of the methods of express control of the composition and quality of the milk produced. It is difficult to imagine a modern farm without automated solutions such as vacuum milking machines, automatic feeders, etc. To ensure product quality control, farms are increasingly using high-tech express analysis systems, which are gradually replacing the classic, expensive invasive chemical methods. However, chemical analysis methods still dominate the manufacturing environment, although they cannot provide the required online analysis. Among high-tech modern methods, analyzers based on optical spectroscopy in both reflection [7] and absorption [8] modes are especially widespread and very popular in agriculture. In particular, the use of infrared spectroscopy in the visible (Vis) 400–800 nm, near infrared (NIRS) 800–2500 nm, and mid-infrared (MIRS) 2500–15,000 nm ranges, as well as their combination, allows one to quickly and contactlessly assess the composition products and adjust the production process. Spectroscopic methods are widely used in agriculture

for various purposes, such as: obtaining information on the composition of products [9], fertilizer content, the composition of the feed base for animals [10,11], the composition of the soil [12], and the level of ripeness of the crop [13]. The most important advantage of modern optical analyzers used on the farm is their portability against the background of high accuracy, the speed of data, acquisition, and non-invasiveness. The quality and volume of dairy products produced depend on the composition and balance of the feed consumed by animals. In this regard, special attention is paid to the control of feed for farm animals. Of great interest is the use of the so-called remote sensing of pastures and fields with forage crops using unmanned and manned aerial vehicles. The creation of maps based on the obtained data allows for the predicting of changes in soil composition and for optimizing fertilization. The development of real-time monitoring tools for the composition of milk produced in production is also an extremely demanded task. Unfortunately, most milk analyzers are stationary and require preliminary preparation of the analyzed sample. Stationarity leads to a time delay between the receipt of the object under study and its analysis. Sample preparation affects the accuracy of the analysis due to the use of reagents, conservation, or freezing of the sample. The use of optical analyzers allows one to solve these problems and provide a quick adjustment to the production process. In this review, we consider the main spectral methods used in modern livestock farming. The focus of the review is aimed at comparing various analysis methods, instruments, and their prototypes operating in the visible, near, and middle infrared regions.

2. Variety of Optical Techniques Used in Agricultural Applications

Optical diagnostic methods are of great interest, since these methods have a high analysis speed, and also make it possible to diagnose an object by a non-contact method. All optical methods of analysis can be divided into two main categories: non-spectral and spectral (Figure 1). Using spectral methods, the spectrum of interaction of the object under study with electromagnetic radiation is recorded. The spectrum is the dependence of the radiation intensity on the wavelength, frequency, or wavenumber. Non-spectral methods are based on measuring the intensity of absorbed, emitted, reflected, or scattered light, as well as on the degree of its coherence. The main non-spectral methods include scatterometry (measurement of the specific effective scattering area), reflectometry (measurement of reflection loss), and refractometry (measurement of the refractive index). Currently, spectral methods are more often used for analysis, such as: emission spectral analysis (based on the analysis of emission or absorption spectra of radiation), absorption spectroscopy (based on the study of absorption spectra of the test substance), as well as analysis of the Raman scattering spectra of a substance [14] and, finally, the luminescent method of analysis [15]. Absorption spectroscopy, or absorption and transmission spectroscopy, makes it possible to simultaneously obtain the qualitative and quantitative composition of the object under study, and also provides information on the chemical nature of the substance. This method of analysis is characterized by high speed, high sensitivity, and the ability to analyze substances in all states of aggregation. The location of the “bands” in the obtained absorption spectrum carries information about the qualitative composition of the sample, and the intensity of the bands carries information about the concentration of the corresponding component [16]. A commonly used method for diagnosing biological objects, in particular, liquids (milk, blood, etc.), is optical spectroscopy in the near and far infrared region (MIRS and NIRS). MIR spectroscopy allows for the identification of vibrational transitions and covers the spectral range from 2500 to 50,000 nm ($4000\text{--}200\text{ cm}^{-1}$) [17]. Spectroscopy in the near infrared range (NIR; 800–2500 nm; $10,000\text{--}4000\text{ cm}^{-1}$) allows one to obtain information about the molecules of the sample under study by measuring absorption bands resulting from overtones and combined excitations [18]. All molecules containing a hydrogen atom have a measurable spectrum in the near IR region, which contributes to the fact that a wider range of organic materials is suitable for analysis in the near IR range than for analysis in the mid IR range [17].

Figure 1. The main methods of optical diagnostics used on dairy farms to analyze the composition of milk and feed.

In a recent review by Evangelista et al. [19], a wide range of agricultural applications of NIR spectroscopy were reported. In particular, modern solutions were considered for assessing the digestibility of the diet by analyzing the chemical-physical composition of raw materials in the general mixed diet and analyzing the chemical composition of slurry and manure. The possibility of using this method for the “online analysis” of milk in the milking parlor was also considered [19].

Depending on the sample under study, the NIRS and MIRS method can be applied in two modes: absorption (transmission) and reflection. When measuring transmission, the detector is placed behind the test sample, which is illuminated by an IR source. The sample should be partially transparent. This type of analysis is often impossible with massive and optically opaque samples. However, when thin samples are available, the transmission imaging mode provides ease of spectra interpretation, improves signal-to-noise ratio, reduces spectral distortion, and increases the correlation between molecular structures and spectral characteristics [20]. To work with plant objects in the transmission mode, preliminary preparation of the sample is carried out; however, this can lead to a change in the native composition and structure of the object. In this regard, for the analysis of plant objects with low transparency, IR spectroscopy in the reflection mode is often used [21–23]. In this approach, the detector and source are placed on the side of the sample to register the signal reflected by the object.

Fourier transform infrared spectroscopy (FTIR) has become especially popular for use in the analysis of biological objects. In a Fourier spectrometer, infrared light passes through the interferometer and then through the sample (or *vice versa*). The FTIR spectrometer simultaneously collects high-resolution spectral data over a wide spectral range. By using the Fourier transform, a more precise analysis of the composition of the sample becomes possible. This gives a significant advantage over a dispersive spectrometer, which measures the intensity in a narrow wavelength range [24]. Thus, the overwhelming majority of modern commercial IR spectrometers operate with Fourier transform, providing accurate analysis with a wide range of investigated components [25].

Presentation of Tabular Data

We analyzed modern literature sources that considered various approaches to assess the composition of milk using optical methods. The data are presented in the form of tables. For milk analysis methods, 50 sources were analyzed. For the analysis of feed, 25 literature sources. When compiling tables (see Tables 1 and 3), we searched for publications over the past 10 years in scientific search systems (machine search), such as Scopus, Web of Science, Google Scholar. When searching for articles, we used sorting by publication year. The search used tags such as “infrared spectroscopy”, “milk analysis”, “feed analysis”, “optical methods”, “MIRs”, “NIRs”, “analyzer”, “forage”, “agriculture”, and their combinations. It is important to note that we did not independently select any separate articles but used only publications offered by the search service.

3. Using Optical Methods for Analyzing the Composition of Milk

Production control of the quality of milk, as well as products made from it, is an important problem in the modern dairy industry. An important task is to create technological solutions for the express analysis of raw milk during milking, without a time delay. Currently, a number of promising optical methods for diagnosing the composition of milk are proposed, including measuring optical density [26], the method of luminescence spectroscopy [27,28], methods of light scattering (scatterometry) [29,30], as well as the method of IR spectroscopy [9,18].

Table 1. Main characteristics of optical methods and devices used to assess the quality of milk.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Flow/Intake	The Investigated Components of Milk	Method Advantages	Prediction Value	Ref.
1	Milkoscan FT + (Foss-Electric A/S, Hillerød, Denmark)	I	NIR-spectroscopy	851–1649	intake	fat, protein, lactose, urea	sufficient and adequate prediction accuracy with regard to fat and protein content in milk was achieved	R ² were 0.998, 0.94, and 0.73 for fat, protein, lactose; 0.31 for urea, respectively	[31]
2	installation: 18 channel multispectral photosensor module and miniature halogen lamp	I	Vis/NIR-spectroscopy	410–940	intake	fat, protein, lactose	high measurement speed, cost-effectiveness of the device and operational efficiency	RPD increased for fat after homogenization from 2.34 to 3.48; for total solids from 2.06 to 2.14	[32]
3	Xethru X4 sensor	C	wideband dielectric spectroscopy (WBDS)	1300–3000	intake	fat	high precision and non-contact application	–	[33]
4	MilkoScan FT + (Foss Electric A/S)	C	MIR-spectroscopy	1300–3000	intake	fat, protein, lactose dry matter, as well as the number of somatic cells	–	–	[34]
5	five in-line, two-stage MIR homogenizers (Delta Instruments) with different homogenization efficiency; LactoScope FTIR Advanced (FTA) milk analyzer equipped with a BMX optical bench (ABB Bomem, MO, Canada)	C	FT-MIR spectroscopy	1300–3000	flow	fat, true protein, anhydrous lactose	homogenization efficiency influenced the results of the assessment of the content of fat and protein	–	[35]

Table 1. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Flow/Intake	The Investigated Components of Milk	Method Advantages	Prediction Value	Ref.
6	MicroPhazir™ NIR Spectrophotometer	C	NIR-spectroscopy	1600–2400	flow	fat, protein, fat-free solids	monitoring in real-time, in-situ and without pre-treatment milk composition, portability, the ability to synchronize between individual devices	R ² for fat, protein, fat-free solids were 0.97, 0.75, 0.61, respectively	[36]
7	Spectral Analyzer AS7262-AS7263	I	NIR-spectroscopy	960–1690	flow	fat, protein, lactose	system can analyze the milk of each individual milking session autonomously; fast online milk analysis, using a real-time prediction model	R ² = 0.989 (fat), 0.894 (protein) and 0.644 (lactose)	[37]
8	MilkoScan FT6000, (Foss, Hillerod, Denmark)	C	MIR-spectroscopy	3359–3612; 5555–5938; 6222–10,799	intake	non-esterified fatty acids (NEFA)	determination of the content of non-esterified fatty acids (NEFA) in the blood of cows using MIR-IR spectroscopy of milk, without blood sampling	R ² values of 0.613 and 0.502, respectively	[38]
9	Portable IR spectrometer MicroPHAZIR™	C	NIR-spectroscopy	1600–2400	intake	protein, fat, fat-free solids, lactose	real-time tracking of quality control parameters for an individual sample	–	[39]

Table 1. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Flow/Intake	The Investigated Components of Milk	Method Advantages	Prediction Value	Ref.
10	MilkoScan Minor, (Foss, Hillerød, Denmark)	C	NIR-spectroscopy	400–900	intake	fat, protein, total solid, lactose	the possibility of using NIR—spectroscopy to assess the genetic variability and heredity of qualitative traits of colostrum	–	[40]
11	Milko-Scan FT1 (Foss Electric, Hillerød, Denmark).	C	FT-MIR spectroscopy	2000–10,800	intake	fat, total protein, casein, lactose, total solids, solids-not-fat	precise definition of milk components for comparison of different genetic groups and breeds of cows	R ² were 0.99 for fat, protein, casein, total solid; 0.97 for lactose; 0.94 for solids-not-fat	[41]
12	LactoScope FTIR Advanced; five different homogenizers	C	FT-MIR spectroscopy	1300–3000	intake	fat	predicting the particle size of fat globules in homogenized milk	–	[42]
13	MilkoScan FT 120 (FOSS, Hillerød, Denmark; Milcom Servis as, (Prague, Czech Republic)	C	MIR-spectroscopy	1300–3000	intake	determination of preservatives content in milk	–	–	[43]
14	installation: probe with eight fiber optic channels with a diameter of 200 µm, forming a linear array	I	Vis/NIR-spectroscopy	400–995	intake, flow	fat, total protein	alternative to full-scale scanning or diode array spectroscopy	R ² for fat 0.97; for protein 0.84	[44]

Table 1. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Flow/Intake	The Investigated Components of Milk	Method Advantages	Prediction Value	Ref.
15	MilkoScan FT120 (Foss, Hillerød, Denmark)	C	Vis/NIR spectroscopy dispersion-based	400–1100	intake, flow	fat, total protein	the generated PLS regression models were trained on a very large set of milk samples; the accuracy of the resulting models makes them suitable for many practical applications in the dairy industry	R ² for fat was 0.95; for protein was 0.77 (PLS)	[45]
16	NIR spectrometer MP.0331.04, (Bruker Co., Bremen, Germany)	C	FT-NIR spectroscopy	833–2500	intake	fat, total protein	PLSR-UVE-PLS model had excellent protein prediction for non-homogenized milk	RPD when using the PLCR model for protein determination, before homogenization was 2.22; after 2.73	[46]
17	Horiba LA-920; (Horiba Instruments Inc., Irvine, CA, USA)	C	Laser scatterometry, Vis/NIR-spectroscopy	360–970	intake, flow	fat, fatty acid profile, protein, lactose	the device provides the ability to take multiple samples during milking without losing vacuum or interrupting intermediate milk sampling	R ² for fat, protein, lactose was 0.94; 0.92; 0.84	[47]
18	IR spectrophotometer with a diode matrix in the diffuse transmission mode; glass cavity with an internal path length of 4 mm	I	NIR-spectroscopy	400–1100	intake	fat, total protein	variety and relative cheapness of components, high design flexibility	R ² = 0.9 for fat and protein	[48]

Table 1. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Flow/Intake	The Investigated Components of Milk	Method Advantages	Prediction Value	Ref.
19	TIDAS E oT J&M Analytik AG, Esslingen, Germany) in diffuse transmission mode through a 4 mm cuvette	C	Vis/NIR-spectroscopy	400–1100	intake	fat, protein	the method shows the influence of the size distribution of fat globules on the diffuse transmission spectra	–	[49]
20	FTLA 2000 (ABB, Saint-Laurent, QC, Canada) with thermostat and light transmission control	C	FT-NIR-spectroscopy	780–2500	intake	<i>Escherichia coli.</i> , <i>Pseudomonas aeruginosa</i>	NIRS can be used to detect and quantify pathogenic bacteria and bacteria that cause milk spoilage	R ² for <i>E. coli</i> was 0.94; for <i>P. aeruginosa</i> 0.60	[50]
21	testing data from two anonymous MIR instruments	I	MIR-spectroscopy	1300–3000	flow	fat, protein, dry matter	a statistical approach has been developed to determine the differences from the obtained values between the two instruments	–	[51]
22	MilkoScan FT-120, Foss (Foss A/S, Hillerød, Denmark); Near Infra-Red Multipurpose Analyzer (MPA) Bruker Optik GmbH (Ettlingen, Germany)	C	FT-MIR and FT-NIR spectroscopy	800–2500; 2500–15,000	intake	lactose, protein, fat, total solid	near and mid-infrared spectroscopy methods are both valuable for raw milk analysis	Correlation coefficient ≥ 0.96 for protein, $r \geq 0.99$ for fat, $r = 0.82$ for lactose; $r = 0.90$ for total solid	[52]

Table 1. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Flow/Intake	The Investigated Components of Milk	Method Advantages	Prediction Value	Ref.
23	installation combining measurements of transmission, scattering and fluorescence spectra of milk; halogen and deuterium lamps, optical fiber system, AvaSpec 2048 spectrometer with 8 nm resolution	I	Vis/NIR-spectroscopy	300–1100	intake	fat, protein, carbohydrates, minerals, calories	fluorescence and scattering spectra of milk can be used for the identification of different producers of milk and for obtaining information about milk chemical composition	–	[53]
24	Milkoscan (Foss Electric, Hillerod, Denmark)	I	NIR-spectroscopy	700–1050	flow	fat, protein, lactose, somatic cells	the NIR spectroscopic sensing system developed in this study can be used for online real-time monitoring of fat, protein, lactose and somatic cells	R ² were 0.98; 0.72; 0.54; 0.63 for fat, protein, lactose, somatic cells, respectively	[54]
25	AfiLab (Afimilk, Kibbutz Afikim, Israel); Bentley 2000 (Bentley Instruments Inc., Chaska, MN, USA)	C	MIR-spectroscopy; NIR-spectroscopy	300–950; 1300–3000	intake, flow	fat, anhydrous lactose, protein, total solids content	AfiLab real-time milk analyzers can be useful for assessing the content of milk components	–	[55]
26	Milkoscan FT + (Foss A/S, Hillerod, Denmark), reflection/transmission mode;	C	MIR-spectroscopy; NIR-spectroscopy	400–1000; 11,000–2500	intake	fat, crude protein, lactose, urea	transmission spectroscopy can be used to predict the three main components of milk, but with less accuracy for fat and crude protein than in reflection mode	reflection: R ² for fat and protein was >0.95; for lactose was <0.75; transmission: R ² for fat and protein was >0.9; for lactose was 0.88;	[7]

Table 1. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Flow/Intake	The Investigated Components of Milk	Method Advantages	Prediction Value	Ref.
27	MilkoScan FT6000 (Foss Electronic A/S)	C	FT-MIR-spectroscopy	2000–12,000	intake	fat, protein, lactose	using modern statistical machine learning methods to predict features based on mid-infrared spectroscopy can improve prediction accuracy	R ² were 0.65 for pH; 0.5 for rennet coagulation time; 0.2–0.5 for protein; <1 for casein micelle size	[56]
28	MilkoScan FT6000 (Foss Electric A/S, Hillerod, Denmark)	C	MIR-spectroscopy	2000–15,000	intake	fatty acid composition, protein, lactoferrin, Ca, P, Mg, K	the use of various models for forecasting the composition	–	[57]
29	MilkoScan FT6000 (Foss Electric A/S, Hillerod, Denmark)	C	MIR-spectroscopy	2000–15,000	intake	fatty acid profile, protein composition, lactoferrin, concentration of basic minerals	high accuracy of the profile of fatty acids in milk	RPD were 1.8–2.0 for fatty acids; 1.6 for protein; 1.8 for fat; 1.3–1.4 for minerals	[58]
30	Milko-Scan FT120 (Foss Electric A/S, Denmark)	C	FT-MIR spectroscopy	2500–12,000	intake	total protein, casein, milk protein composition, β -lactoglobulin, glycosylated κ -casein, whey protein	the use of FT-MIRS to predict the detailed protein composition of milk	RPD were 2.2 for protein; 2.07 for casein; 1.6 for whey protein	[59]

Table 1. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Flow/Intake	The Investigated Components of Milk	Method Advantages	Prediction Value	Ref.
31	Optigraph (OPT; Ysebaert SA, Frépillon, France); MilkoScan FT6000 (Foss Electric A/S, Hillerød, Denmark); Fossomatic FC (Foss Electric A/S) for determining the presence of somatic cells	C	NIR-spectroscopy; MIR-spectroscopy	2000–15,000; 350–1000	intake	fat, protein, casein, lactose	the optical method for analyzing the composition of milk is a good alternative to the mechanical method	correlation coefficients for rennet coagulation time was 0.82; for curd-firming time was 0.49; curd firmness at 30 min was 0.69; for curd firmness at 45 min was 0.41	[60]
32	MilkoScan FT 6000 (Foss Electric A/S, Hillerød, Denmark)	C	MIR-spectroscopy	2000–15,000	intake	fat, fatty acid profile, total protein, casein, lactoferrin, Ca, P, Mg, K	MIR spectroscopy is suitable for evaluating genetic parameters	$R^2 < 0.5$ for minerals; 0.2–0.7 for rennet coagulation time; 0.7 for fat; 0.8 for casein; 0.42 for lactoferin	[61]
33	MilkoScan FT 6000 (Foss, Hillerød, Denmark)	C	MIR-spectroscopy	2000–12,000	intake	fat, fatty acid profile	the use of MIR spectroscopy for the evaluation of fatty acids; using six different data processing methods	RPD were 21.8, 19.4, 24.0, 22.2, 22.4, and 21.1 for 1–6 methods, respectively	[62]
34	handheld spectrometer 4100 EXOSCAN (Agilent Technologies); tabletop Nicolet™ iS10 FTIR (Thermo Scientific™)	C	FT-MIR	2500–15,384	intake	proteins, fats, carbohydrates	handheld FT-MIR—a good alternative to the benchtop analyzer for the analysis of macrocomponents in milk	Benchtop: R^2 were 0.96; 0.90; 0.92 for fats, proteins, and carbohydrates, respectively (PLS models) Portable: R^2 were 0.91; 0.69; 0.86 for fats, proteins, and carbohydrates, respectively (PLS models)	[63]

Table 1. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Flow/Intake	The Investigated Components of Milk	Method Advantages	Prediction Value	Ref.
35	Spectrum GX, (Perkin-Elmer Ltd., Beaconsfield, UK) equipped with a DTGS detector	C	FTIR spectroscopy combined with 2D correlation IR spectroscopy	2500–25,000	intake	determination of different types of carbohydrates, incl. lactose	quick and convenient way to assess the quality of milk powder	Correlation coefficients were 0.97–0.99	[64]
36	FTIR spectrometer with diamond/ZnSe crystal cell ATR (RX-1 Perkin Elmer, MA, USA)	C	FT-IR-spec-troscopy	2500–25,000	intake	fat, proteins, carbohydrates	accurate forecast using PLS-DA model	R ² = 0.958	[65]
37	Milko-Scan FT120 (Foss Electric A/S, Hillered, Denmark)	C	FT-MIR spectroscopy	2500–11,110	intake	casein	the possibility of predicting the properties of milk coagulation and acidity of milk using MIR spectroscopy in combination with PLS regression was shown	R ² for titratable acidity was 0.66; rennet coagulation time and pH were 0.59–0.62	[66]
38	MPA Multi Purpose FT-NIR Analyzer (Bruker, Germany)	C	MIR/NIR spectroscopy	1110–2500	intake	melamine	fast, sensitive, reliable, and inexpensive method for the analysis of liquid milk	–	[67]
39	MilkoScan FT 6000 (Foss Electronic A/S, Hillered, Denmark)	C	MIR-spectroscopy	2000–11,110	intake	protein, fat, casein, urea, dry matter	fast and inexpensive milk quality control using MIR-spectroscopy	R ² = 0.73 for pH; 0.61 for rennet coagulation time	[68]
40	CombiFoss FT+ analyzer (FOSS, Hillerød, Denmark)	C	FT- MIR spectroscopy	1996–10,810	intake	fat, protein, lactose, urea, β -hydroxybutyrate	a methodology of spectral analysis was developed to study the relationship between animal welfare and milk FTIR spectral data	–	[69]

Table 1. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Flow/Intake	The Investigated Components of Milk	Method Advantages	Prediction Value	Ref.
41	Ultra-compact spectrometer Micro-NIR 1700 (JDSU, Milpitas, CA/USA); desktop NIRFlex N-500 (Buchi AG, Flawil, Switzerland)	C	FT-NIR-spectroscopy	908–1676 (Micro-NIR 1700); 1000–2500 (NIRFlex N-500)	intake	fatty acid profile	a new method is presented for organic milk authentication by portable NIR spectroscopy	Correlation coefficients were 0.1–0.4 for different fatty acids	[70]
42	Bentley Instruments NexGen Series FTS Combi machine (Chaska, MN, USA)	C	MIR-spectroscopy	2500–15,408	intake	fat, protein, lactose	determination of the pregnancy status of dairy cows using MIRS analysis of the composition of milk	–	[71]
43	CARY 5G UV/VIS/NIR	C	NIR-spectroscopy	1027–2400	intake	starch, whey, sucrose	LS-SVM models were built with low prediction errors and superior performance compared to PLS	LS-SVM: R^2 for starch, whey and sucrose were 1.0; PLS: R^2 were 0.99, 0.98, and 0.99, respectively	[72]
44	MilkoScan FT7	C	MIR-spectroscopy	2000–15,000	intake	fat, total protein, casein, lactose, urea nitrogen, β -hydroxybutyrate	analysis of the content of metabolites in the blood based on the obtained spectra of milk	coefficients of determination for β -hydroxybutyrate, urea, and non-esterified fatty acids were 0.63, 0.58, and 0.52, respectively	[73]
45	Milko-Scan FT120 equipped with a Fourier transform infrared interferometer	C	MIR-spectroscopy	2000–15,000	intake	fat, protein, casein	the method makes it possible to predict the coagulation parameters of milk using MIR methods	R^2 were 0.6 for rennet coagulation time; 0.5 for curd firmness	[74]

Table 1. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Flow/Intake	The Investigated Components of Milk	Method Advantages	Prediction Value	Ref.
46	model 6500 NIRS scanning spectrometer (Foss NIR Systems)	C	Vis/NIR-spectroscopy	400–2500	intake	fat, protein	the approach can be used to authenticate dairy products	–	[75]
47	MilkoScan FT6000 (FOSS Analytical A/S, Hillerød, Denmark)	C	FT-MIR-spectroscopy	2000–15,000	intake	fat, total protein, lactose, casein, acetone (Ac), acetoacetate (AcAc), β -hydroxybutyrate (BHBA)	the milk analyzer can be calibrated to detect subclinical ketosis, which allows for additional assessment of the health of the herd	Correlation coefficient for Ac and BHBA was 0.8	[76]
48	the system consisted of an NIR spectroscopic instrument, a milk flow meter, a milk sampler	I	NIR-spectroscopy	600–1050	flow	fat, protein, lactose, somatic cells, urea nitrogen	NIR spectroscopy can be used for on-line monitoring of fat, protein, lactose, somatic cells and urea nitrogen during milking using a milking robot with sufficient accuracy	R ² for fat, protein, lactose and somatic cells were 0.95; 0.72; 0.83, and 0.68, respectively	[77]
49	Matrix-F FT-NIR, (Bruker, Germany)	C	FT-NIR-spectroscopy	800–2500	flow	fat, protein, total solid content	FT-NIR flow technology has demonstrated accurate, reliable, and consistent performance	Correlation coefficient were 0.96 for fat; 0.85 for protein; 0.96 for total solid; RPD were 5.1, 2.2, 1.3, respectively	[78]

Table 1. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Flow/Intake	The Investigated Components of Milk	Method Advantages	Prediction Value	Ref.
50	Brüker Equinox 55 IR spectrometer using deuterated triglycine sulfate (DTGS) detector (Brüker Ltd., Coventry, UK)	C	FT-IR-spectroscopy	2500–20,000	intake	<i>Staphylococcus aureus</i> , <i>Lactococcus lactis ssp. cremoris</i>	FT-IR spectroscopy made it possible to fairly well assess the levels of <i>S. aureus</i> and <i>L. lactis</i> in both pure form and in co-cultures	R ² varied on average from 0.78 to 0.88	[79]

* C—commercial equipment; I—installation, developed in laboratory; R²—coefficient of determination; RPD—the ratio of performance to deviation.

Below is a table containing the reviewed literature, which discusses various approaches taken to assess the composition of milk (Table 1). We considered each article according to the following parameters: analyzer characteristics, analysis method, spectral range, ability to work in a stream, determined components, advantages of the method, and a short conclusion for each work. In addition, we indicated the prediction value (R^2 or RPD) for the used model. We also conducted a formal analysis of the data in Table 1 and presented the main patterns in the form of infographics (Figure 2).

Figure 2. Comparison of the main characteristics of milk analyzers: (A) Distribution of devices according to the analyzed characteristics of milk; TC—Technical characteristic; (B) Distribution of devices according to the used frequency range; (C) Allocation of analyzers by parameter flow/sampling.

The most frequently analyzed components characterizing the quality of the test milk were the concentrations of fat (~40% of total), total protein (~35%), carbohydrates (lactose) (~20%) [64], and specific protein casein (~10%) [41] (Figure 2A). There are also studies in which, using spectral methods, urea, and some technical characteristics are detected, for example, liquid flow rate, gas content, etc. A small number of studies using IR spectroscopy considered the possibility of identifying somatic and bacterial cells in milk [34,60,77]. The physiological norm for the content of somatic cells in milk is considered to be from 100 to 500 thousand per mL [80]. An increase in the number of somatic cells (cells of the cylindrical, squamous, and cubic epithelium of the mammary gland, leukocytes, erythrocytes) in milk is a marker of the development of mastitis in an animal [81]. The problem of the early detection of mastitis is quite acute in the modern dairy industry. Cámara-

Martos et al. [50] reported the detection of *E. coli* and *P. aerogenosa* cells by FT-NIRS. Moreover, Nicolaou et al. [79] using FT-IRS, were able to determine the level of *S. aureus* and *Lactococcus lactis* ssp. *cremoris* both in pure form and in cocultures, as well as the cells of other lactococci and enterococci *L. lactis*, *E. durans*, *E. faecalis*, and *E. faecium* [82]. It has also been reported that it is possible to detect impurities in milk using MIR/NIR spectroscopy, in particular, melamine [67], starch, and sucrose [72].

A significant problem in the analysis of raw milk is the aggregation of fat micelles and protein globules, which prevent accurate diagnosis due to scattering [83]. The presence of water in milk complicates the NIR spectroscopic analysis, and also interferes with the analysis of the presence of micro- and macrobubbles of gases in milk [84].

Milk is a complex colloidal system. The content of the main elements in the composition of cow's milk may vary depending on the individual physiological characteristics of the animal, the season, lactation period, conditions of detention, as well as the breed of the animal. However, on average, cow's milk contains 4.7–4.9% lactose, which is in a dissolved state; ~3.6% fat in the form of emulsified globules [85]; 3.4% protein, with a predominance of casein (about 80%) in the form of micelles, as well as β -lactoglobulin and lactoglobulin. Nitrogen in milk (N) is found in two main fractions-true protein and NPN (non-protein nitrogen). True protein makes up 95%, NPN makes up the remaining 5% of the total nitrogen in milk. NPN is approximately 30–35% milk urea, 25% creatinine/uric acid, 15% amino acids, and 10–30% ammonia [86]. The concentration of urea, the main fraction of NPN, in milk is normally about 14.2 mg/100 g of milk (~5 mM) [87]. Milk also contains minerals in the form of salts, also known as ash (~0.7%), the main anions of which are chloride, phosphate and citrate, and the cations are sodium, calcium, and magnesium. Milk contains a complex of fat-soluble (A, D, E, K) and water-soluble (B, C) vitamins [86]. Below is a table that lists the main components in the composition of cow's milk in percentage terms (Table 2).

Table 2. Main components of cow milk (adapted from [85,88,89]).

Component	%
Water	85.5–89.5
Fat	2.5–6.0
Protein	2.9–5.0
Lactose	3.6–5.5
Minerals	0.6–0.9
Urea	<1%
Atypical components (impurities)	
β -hydroxybutyrate	<1%
Starch	<1%
Sucrose	<1%
Melamine	<1%

Milk contains about 88% water, which leads to the appearance of pronounced bands in the near infrared range of around 960, 1440, 1950, and 2076 nm, which overlap with some bands of milk components [52,75]. In MIRS, the first band of water overlaps with much smaller bands characteristic of the amide I and amide II bands of proteins located in the ranges 5882–6250 nm and 6369–6451 nm, respectively [90]. One of the most common approaches to increasing the accuracy of milk analysis is to pre-homogenize it. It was shown that the use of homogenization increases the accuracy of predicting the content of fat and protein in milk and does not affect the accuracy of the determined lactose [35]. It was also found that homogenization improves the accuracy of predicting protein content

in milk using FT-NIR spectroscopy [46]. A number of works have also considered the possibility of determining the profile of fatty acids in milk by the MIRS method [62,91].

A known example is the use of FT-MIR spectroscopy of milk for the early diagnosis of ketosis in cows. Clinical and subclinical ketosis leads to an increase in the concentration of ketone bodies in blood and milk: acetone (Ac), acetoacetate (AcAc), and β -hydroxybutyrate (BHBA). De Roos et al. [76] reported the successful detection of Ac and BHBA in milk by FT-MIRS using a developed calibration model. The ability to detect ketone bodies in the milk taken is a very important parameter of the analyzer, since it allows the diagnosis of ketosis in individual cows at an early stage without blood sampling.

As seen in Figure 2B, the most popular method for assessing milk quality is mid-infrared IR spectroscopy (~50% of sources reviewed). About 40% of all methods and devices work in the near infrared range. Only about 10% of devices operate in the visible or UV range. Raw milk can be analyzed in both reflection and IR absorption modes. It was previously shown that, for NIRS (1100–2500 nm) analysis of the transmission spectrum of milk, a minimum optical path length (0.5–1 mm) is required [92,93]. Aernouts et al. [7] compared Vis/NIR reflectance and transmission spectroscopy for the analysis of fat, protein, and lactose, as well as urea in milk. The Vis/NIR reflectance spectra allowed very accurate control of the fat and protein content in raw milk, however did not allow an accurate prediction of the lactose content. In contrast, the transmission spectra of milk samples allowed for accurate predictions of fat, crude protein, and lactose contents. At the same time, none of the approaches made it possible to determine the content of urea in milk [7]. As is known, the level of Milk Urea Nitrogen (MUN) is an important indicator of the protein diet of dairy cows [94,95]. Low MUN content results in reduced milk yield. In this regard, the ability to control the MUN content in milk allows one to adjust the diet of animals on a dairy farm. Only in ~6% of the sources reviewed by us was the level of urea in milk successfully determined. In particular, Kawasaki et al. [77] developed an NIRS system for real-time milk analysis, which allows for the assessing of the content of not only the three main components of milk (fat, lactose protein), but also urea nitrogen.

It is interesting to note the portable and laboratory (bench-top) IR spectrometers compared in several works. The results obtained from portable devices were in good agreement with the results obtained using bench-top analyzers [63,70]. Moreover, several studies have noted the possibility of assessing the technological characteristics of milk, such as rennet coagulation time and curd compaction time, using IR spectroscopy [57,58,68].

As is well known, the method of IR spectroscopy requires the accurate calibration and selection of the optimal algorithm for interpreting the obtained spectra. The most commonly used models are those built using Partial Least Squares regression (PLS) [45,72]. The use of more complex models with preliminary processing of spectral data makes it possible to obtain a more accurate prediction of the content of components in milk. For example, Soyeurt et al. [62] considered the application of six different mathematical methods for preprocessing IR spectra to accurately determine the content of fatty acids in milk samples. Moreover, Bonfatti et al. [57] used various models to predict milk composition using the MIRS method, including Partial Least Squares Regression (PLSR) and Bayesian models. Differences in prediction accuracy between PLSR and Bayesian regression models were zero or insignificant after noise reduction using spectral-mathematical processing. Finally, in a recent report by Frizzarin et al. [56] a statistical machine learning method was used to obtain a more accurate prediction of milk content when analyzed using MIRS compared to PLSR.

Often during laboratory analysis, to preserve the quality of milk, it is frozen, or preservatives are added. Zajac et al. [43] reported that the addition of preservatives (potassium dichromate, azidiol, bronopol) at concentrations of 0.1%, 0.5%, and 1% resulted in significant deviations in MIRS results after 24 h after adding. The use of flow-through milk analyzers integrated into the milking system makes it possible to solve the problem with the transportation and storage of milk in a laboratory analysis approach [37]. Unfortunately, only a small fraction of currently existing commercial milk analyzers operate in line mode.

In ~80% of the literature reviewed by us, laboratory analyzers working with preselected samples were used (Figure 2C).

Thus, the use of IR spectroscopy, including FTIR, in the near and middle spectral ranges is a widely used diagnostic method in the dairy industry. This approach is used mainly to assess the content of three main components in milk that determine its energy value and quality (fat, protein, and lactose). In some cases, spectral methods can identify important markers of animal diseases, and can also be useful for optimizing the production process. The integration of IR transmission spectroscopy into milking systems is hampered by the need to use a thin layer of milk, which leads to a decrease in the speed of its pumping. Reflectance IR spectroscopy solves this problem. However, for a more accurate determination of some components of milk, the development of new methods is required, as well as the improvement of existing calibration models for processing spectral data for existing methods.

4. Application of IR Spectroscopy to Analyze the Quality of Feed

The composition of vegetable feed that forms the diet of agricultural animals is an important factor in the productivity of dairy farming. We have analyzed modern literary sources devoted to the study of the use of IR spectroscopy for the diagnosis of feed for farm animals (see Table 3). Near infrared reflection spectroscopy (NIRS) is predominantly used for feed analysis (~90% of the sources we reviewed), and only ~10% of the studies used MIRS analysis (Figure 3A). The most important and often analyzed components of feed for farm animals, which determine their energy value and digestibility, are the content of crude protein (CP), fats, neutral-detergent fiber (NDF), acid-detergent fiber (ADF), water soluble carbohydrates (WSC), as well as total nitrogen (N) (see Figure 3B). Acid Detergent Fiber (ADF), a cellulose and lignin, is an important parameter of feed quality that negatively correlates with feed digestibility [96]. The NDF parameter is the total mass of plant cell walls, consisting of the ADF fraction and hemicellulose. NDF values are also an important characteristic of feed, as they reflect the amount of plant feed that an animal can consume. Typically, as the proportion of NDF increases, dry matter intake tends to decrease. These components have been successfully identified using NIRS for alfalfa (*Medicago sativa*) [97], Italian ryegrass (*Lolium multiflorum*) [98], willow (*Salix* spp.) [99,100], corn (*Zea mays*) [21,101], sorghum (*Sorghum bicolor*) [102], and other plants used as feed for farm animals. NIR is most sensitive to vibrations of covalent bonds of hydrogen atoms with atoms of other chemical elements. As is known, organic molecules of plant biopolymers are rich in covalent bonds C-H, O-H, and N-H [103]. However, the absorption of NIR by water strongly overlaps most of the NIR spectrum of biomolecules [104]. In this regard, for a more accurate analysis of a plant feed sample using NIRS in laboratory conditions, it is usually pre-dried and milled [105,106]. It is important to note the possibility of detecting toxins in the feed composition using NIRS. The possibility of detecting hydrogen cyanide in fodder sorghum (*Sorghum bicolor*) using an NIRS analyzer was shown by Fox et al. [102].

The IVDMD method (in vitro dry matter digestibility) and the IVOMD method (in vitro organic matter digestibility), also well known as the Tilley and Terry method [107], are commonly used to assess the nutritional value of feed for ruminants. IVOMD and IVDMD are determined by subtracting organic matter (OM) and dry matter (DM) residues from the original values before fermentation in rumen fluid, respectively. Samadi et al. [108] considered the possibility of predicting the nutritional value of feed from residues from the food industry using the analysis of NIR spectra. Moreover, Zgouz et al. [109] reported the possibility of determining IVOMD using eight different commercial portable spectrometers.

Table 3. Main characteristics of optical methods and devices used to assess the quality of feed.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Object	The Investigated Parameters of Feed	Method Advantages	Prediction Value	Ref.
1	Thermo Fisher Scientific Nicolet 5700 equipped with Smart iTR TM Attenuated Total Reflectance sampling device	C	ATR-FT-MIR spectroscopy	2500–14,815	ryegrass, white clover, chicory, plantain	DM, hemicellulose	portable method for analysis of feed composition	R ² were 0.92 and 0.86 for hemicellulose and neutral detergent fiber, respectively	[23]
2	spectrometer with an array of micromirrors and a single-element detector	I	NIR-spectroscopy	800–2500	lucerne	CP, NDF, ADF	a high-performance portable NIR spectrometer with an embedded chemometric model has been developed to extract the necessary information about the quality of feed	R ² were 0.516, 0.742, 0.704, for CP, ADF, NDF, respectively	[97]
3	-	I	NIR-spectroscopy	1000–2500	fermented sago residues	NDF, ADF, in vitro dry matter digestibility (IVDMD), in vitro organic matter digestibility (IVOMD)	excellent results for IVDMD, IVOMD, and NDF predictions have been achieved	RPD were 2.78 for IVDMD; 2.35 for IVOMD; 2.31 for NDF; 3.00 for ADF	[110]
4	Bruker MPA (Bruker, Bremen, Germany)	C	FT-NIR-spectroscopy	800–2500	Italian ryegrass (<i>Lolium multiflorum</i>)	CP, ADF, NDF, WSC	four optimal NIRS models have been developed to predict CP, NDF, ADF, and WSC content in Italian ryegrass samples	RPD for CP 8.58; for NDF 4.25; for ADF 3.64; for WSC 3.10	[98]

Table 3. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Object	The Investigated Parameters of Feed	Method Advantages	Prediction Value	Ref.
5	FOSS NIRSystems 5000 (FOSS NIRSystems, Silver Spring, MD); PoliSPEC NIR PL1 and PL2 (ITPhoton-ics, Breganze, Italy)	C	NIR-spectroscopy	1100–2500 (FOSS NIRSystems 5000); 902–1680 (PoliSPEC NIR)	corn silage	DM, ash, CP, NDF, ADF, starch, total sugar (TS)	poliSPECNIR PL2 gave more accurate predictions of feed composition than PL1	0.72 > R ² < 0.97 for DM, ash and NDF; 0.78 > R ² < 0.82 for CP and ADF	[101]
6	eight kinds of handheld spectrometers: DLP NIRscan Nano EVM, F750, LabSpec 4, MicroNIR1700, MicroNIR2200, NI-RONE 2.2, Scio, TellSpec	C	NIR-spectroscopy	350–2500 (LabSpec 4); 901–1701 (NIRscan Nano EVM); 450–1140 (F750); 908–1676 (MicroNIR1700); 1158–2169 (MicroNIR2200); 1750–2150 (NIRONE 2.2); 740–1070 (Scio); 900–1700 (TellSpec)	<i>Saccharum officinarum</i>	TS, CP, ADF, IVOMD	successful prediction of the composition of dried sugar cane by eight commercial mini-spectrometers with varying accuracy	R ² for TS: DLP NIRscan 0.86; F750 0.72; LabSpec 4 0.97; MicroNIR1700 0.94; MicroNIR2200 0.97; NIRONE 2.2 0.79; Scio 0.68; TellSpec 0.69; R ² for CP: DLP NIRscan 0.65; F750 0.87; LabSpec 4 0.92; MicroNIR1700 0.91; MicroNIR2200 0.89; NIRONE 2.2 0.90; Scio 0.87; TellSpec 0.73	[109]
7	NIRSystems 6500 scanning monochromator (FOSS, Silver Spring, MD, USA) with a transportmodule	C	NIR-spectroscopy	400–2500	Meadow grasses	total N; nitrogen in the substance precipitated by trichloroacetic acid; insoluble nitrogen in borate-phosphate buffer; insoluble nitrogen in neutral detergents; acid detergent insoluble nitrogen (ADIN)	accurately predicted the content of total nitrogen, nitrogen in the substance precipitated by trichloroacetic acid, and nitrogen insoluble in neutral detergents	R ² were 0.97 for total N; 0.91 for nitrogen in the substance precipitated by trichloroacetic acid; 0.69 for insoluble nitrogen in borate-phosphate buffer; 0.95 for insoluble nitrogen in neutral detergents; 0.74 for ADIN	[10]

Table 3. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Object	The Investigated Parameters of Feed	Method Advantages	Prediction Value	Ref.
8	FieldSpec Pro (Analytical Spectral Devices, Incorporated)	C	NIR-spectroscopy	350–1050	<i>Salix</i> spp.	CP, NDF, ADF, acid detergent lignin, acid insoluble ash, tannins, digestible protein (DP), digestible dry matter (DDM)	feed quality indicators such as DP and DDM can be successfully quantified using hyperspectral remote sensing data	R ² were 0.81 for DP; 0.73 for DDM;	[99]
9	Unity Spectrastar 2500X rotating top window system (Unity Scientific, Milford, MA, USA)	C	NIR-spectroscopy	680–2500	herbs, legumes	total N, CP, NDF, ADF	broad calibrations predict the performance of annual grasses, annual legumes, and forbs more accurately than perennial grasses or legumes	RPD were 5.3 for CP; 4.3 for NDF; 3.7 for ADF; 2.2 for organic matter	[111]
10	benchtop-type (FOSS) and two handheld NIR devices (microPHAZIR and DLP NIRscan Nano EVM)	C	NIR-spectroscopy	1100–2498 (FOSS); 1600–2400 (microPHAZIR); 900–1700 (DLP NIRscan)	<i>Panicum virgatum</i> L., <i>Cynodon dactylon</i> (L.)	CP, ADF, NDF, IVTD	the ability to predict component content for both handheld devices was similar to that of a desktop device	R ² were 0.81–0.87 for NDF; 0.96–0.99 for CP; 0.84 for ADF; 0.9–0.97 for IVTD	[112]
11	NIRSystem 6500 (Foss NIRSystems, Inc., Silver Spring, MD, USA)	C	NIR-spectroscopy	400–2498	<i>Sorghum bicolor</i> (L.) Moench × <i>Sorghum sudanense</i> Stapf. cv. <i>Superdan</i>	hydrogen cyanide (HCN)	possibility of using NIR to predict HCN content in feed sorghum	PLS model: R ² = 0.838; multiple linear regression (MLR) approach: R ² = 0.847	[102]
12	SVC HR 1024-i, (Spectra Vista Corporation, Poughkeepsie, NY, USA)	C	vis-NIR-spectroscopy	350–2500	herbal crops of mountain pastures	ash, fat, protein, fiber	fast, economical, and high-performance method for analyzing feed quality	R ² were 0.83 for ash; 0.86 for fat; 0.42 for fiber; 0.93 for protein	[11]

Table 3. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Object	The Investigated Parameters of Feed	Method Advantages	Prediction Value	Ref.
13	SpectraStar 2600 XT-R, (Unity Scientific, Columbia, MD, USA)	C	NIR-spectroscopy	680–2600	<i>Cyamopsis tetragonoloba</i> , <i>Phaseolus acutifolius</i> , <i>Cajanus cajan</i> , <i>Glycine max</i> , <i>Vigna aconitifolia</i>	CP, NDF, ADF, IVTD	NIRS methods can be effective in providing fast and accurate predictions of most feed quality characteristics for various warm-season legumes; machine learning algorithms such as SVM can also develop robust models with relatively few samples	PLS model: R ² were 0.94–0.98 for all forage quality parameters	[113]
14	Foss NIRSystem 6500 (Foss North America, MN); AuroraNir (Grainit srl, Italy); NIR-S-G1 (Innospectra, Taiwan); SCiO (Consumer Physics, Hod Hasharon, Israel)	C	NIR-spectroscopy	1100–2498 (FOSS); 950–1650 (AuroraNir, NIR-S-G1); 740–1070 (SCiO)	<i>Medicago sativa</i> L.	NDF, ADF, ADL, IVTD	portable analyzers AuroraNir and NIR-S-G1 are an alternative to expensive benchtop laboratory equipment, while providing reasonably accurate predictions	AuroraNir: R ² = 0.97 for CP; 0.95 for NDF; 0.96 for ADF; 0.93 for ADL; 0.90 for IVTD; NIR-S-G1: R ² = 0.94 for CP; 0.91 for NDF; 0.93 for ADF; 0.86 for ADL; 0.87 for IVTD	[114]
15	Vector22/N, (Bruker, Ettlingen, Germany)	C	NIR-spectroscopy	833–2500	<i>Zea Mays</i> ssp. L.	% in vitro digestibility, NDF, ADF, CP, Crude Fat	the optimal timing of harvesting corn at the peak of the total assimilable energy was proposed	–	[21]
16	Lambda FTIR-7600 c ATR (Tianjin Gangdong Sci. & Tech. Development Co. Ltd., Nankai, China)	C	FT-MIR-spectroscopy	2500–12,500	ceHo <i>Medicago sativa</i> L.	spectral profiles and chemical properties of protein amides I and II	non-invasive molecular spectroscopy methods are able to detect the features of the internal protein structure of feed	–	[106]

Table 3. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Object	The Investigated Parameters of Feed	Method Advantages	Prediction Value	Ref.
17	NIRS DS2500-FOSS Analytical A/S—Denmark)	C	NIR-spectroscopy	-	<i>Vicia faba</i> , <i>Zea mays</i> var. ICA V-305, <i>Raphanus sativus</i> L., <i>Beta vulgaris</i> , <i>Avena sativa</i> var. Cayuse, <i>Phalaris</i> sp., <i>Medicago sativa</i> L. var. moapa, <i>Medicago sativa</i> L.	DM, CP, NDF, ADF, lignin, hemicellulose, dry matter digestibility and net energy of lactation (ENL)	comparison of nutritional characteristics of different types of forage plants using NIRS	—	[115]
18	UAV with a camera with a spectral sensor Cubert Hyperspectral Fire-flye S185 SE (Cubert GmbH, (Ulm, Germany)	C	vis-NIR-spectroscopy	482–950	hay meadows, <i>Nardus stricta</i> , <i>Lupinus polyphyllus</i>	CP, ADF	the resulting models can accurately estimate the content of crude protein and acid-detergent fiber regardless of the type of pasture; the accuracy of the models is in the same range as the accuracy obtained using field spectroscopy	R ² were 0.33–0.4 for CP; 0.23–0.33 for ADF	[116]
19	Foss NIRSystems model 6500 (Foss NIRSystems, Silver Spring, MD, USA)	C	Vis-NIR-spectroscopy	400–2500	silage	N, NDF, ADF, dry matter digestibility pepsin cellulase (PCDMD)	the developed calibration equations are sufficiently reliable for successful prediction of the considered parameters for permanent grass hayfields	RPD were 7.95, 4.28, 4.23, 5.23 for N, NDF, ADF, PCDMD, respectively	[117]

Table 3. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Object	The Investigated Parameters of Feed	Method Advantages	Prediction Value	Ref.
20	XDS-NIRS rapid content analyzer (FOSS Analytical, Slangerupgade, Denmark)	C	NIR-spectroscopy	400–2498	soybean	CP, crude fat, NDF, ADF	the developed NIR calibration equations are useful for predicting the quality of soybeans according to the considered quality parameters	R ² were 0.92, 0.94, 0.84, 0.78 for CP, CF, NDF, ADF, respectively	[22]
21	Micro-Hyperspec VNIR model, Headwall Photonics, (Bolton, MA, USA)	C	Vis/NIR-spectroscopy	400–850	durum wheat grains <i>Triticum</i> sp.	protein	the use of Vis/NIR-spectroscopy in the form of remote sensing from an airplane made it possible to assess the state of the wheat crop	R ² ≤ 0.21	[118]
22	Foss NIRS model 6500 (FOSS Analytical, Slangerupgade, Denmark)	C	NIR-spectroscopy	400–2500	<i>Salix caroliniana</i>	CP, ADF, NDF, lignin, gross energy (GE), condensed tannin (CT)	accurate prediction of the content of the considered components in the leaves and stems of willow collected in different seasons and years	R ² > 0.75 for CP, ADF, NDF, and GE; R ² = 0.72 for CT	[100]
23	NIRS DS2500 (Foss UK Ltd., Warrington, UK)	C	NIR-spectroscopy	1100–2500	hay, grass, silage	mineral content (Ca, P, K, S, Mg, Na)	the importance of preliminary preparation of the sample under study is shown; drying and grinding of samples increased the accuracy of NIRS analysis	Hay: R ² were 0.31; 0.30; 0.48; 0.41; 0.35; 0.31 for Ca, P, Mg, K, S, Na, respectively	[105]

Table 3. Cont.

N	Analyzer Characteristics	Type (C/I) *	Analysis Method	Spectral Range, nm	Object	The Investigated Parameters of Feed	Method Advantages	Prediction Value	Ref.
24	Thermo Nicolet Antaris II TM	C	NIR-spectroscopy	1000–2500	sago leftovers, coconut flour, soy and ketchup by-products, coffee pulp, cocoa pods, sago tree, ear of corn	IVOMD, IVDMD, NDF, ADF	fast and reliable prediction and determination of several nutritional parameters of animal feeds simultaneously	R ² were 0.75, 0.83, 0.59, 0.61 for NDF, ADF, IVOMD, IVDMD, respectively	[108]
25	MPA, Opus Bruker, (Germany)	C	FT-NIR-spectroscopy	800–2778	grassland plant samples	CP, NDF	significant correlation between NIRS calibration models and reference methods for quantifying pasture quality parameters with greater accuracy in dry samples	dry samples: R ² = 0.936 and RPD = 4.01 for CP; R ² = 0.914 and RPD = 3.48 for NDF; fresh samples: R ² = 0.702 and RPD = 1.88 for CP; R ² = 0.720 and RPD = 2.38 for NDF	[119]

* C—commercial equipment; I—installation, developed in laboratory; R²—coefficient of determination; RPD—the ratio of performance to deviation; TS—total solids; CP—crude protein; ADF—acid detergent fiber; NDF—neutral detergent fiber; IVOMD—in vitro organic matter digestibility; IVDMD—in vitro dry matter digestibility; IVTD—in vitro true dry matter digestibility; DM—dry matter; N—nitrogen; WSC—water soluble carbohydrate; ADL—acid detergent lignin.

Figure 3. Comparison of the main characteristics of feed analyzers: (A) Distribution of devices according to the used frequency range. (B) Distribution of devices according to the analyzed characteristics.

A high carbohydrate content with a very low fat and protein content reduces the quality of the feed. Thus, there is a need for the regular monitoring of pastures in order to control the quality of forage crops. Despite the need to calibrate most analyzers using wet chemistry methods, as well as to develop an accurate model for interpreting spectral data, the use of NIRS is the most optimal and cost-effective [11]. Currently, there are a large number of commercial solutions for FTIR spectral analysis, both for laboratory feed diagnostics and for field use in the form of portable analyzers [97], including those with the ability to register a large area using unmanned aerial vehicles (UAVs) [99,116,120]. In this regard, there are several approaches for measurement: point mapping, linear mapping, terrain mapping using a matrix in the focal plane, and hyperspectral imaging. Point mapping is an analysis at a specific point of an object, followed by movement to another point. Linear display is a collection of spectra in one line and then moving along another parallel line. Terrain mapping using a focal plane array (FPA) allows all spectra to be recorded without moving the sample in a short period of time. Hyperspectral imaging allows one to obtain images at wavelengths in the near infrared range. For this measurement, a large amount of data is collected in a hyperspectral cube, where three axes include two spatial and one spectral axis. This visualization can be created in one of four ways: two-point spectral scanning in a spatial grid pattern, Fourier transform visualization, line-by-line spatial scanning, and wavelength tuning using filters. In this cube, the sample is divided into small areas of surface or volume (called pixels), each representing a full spectrum. A cube is displayed as a three-dimensional matrix or data cube that spans two spatial dimensions (x and y). The third dimension (z) corresponds to the individual wavelength/wavenumber [20,121]. Nowadays, terrain mapping using hyperspectral imaging is increasingly used. In particular, Wijesingha et al. [116] reported successful assessment of CP and ADF content in vegetation cover regardless of pasture type. At the same time, the accuracy of the applied calibration models did not differ from those used in “field” spectroscopy. Thus, remote sensing is a promising tool for assessing feed quality in the field compared to traditional methods, which usually do not provide as detailed information.

The use of portable analyzers can be convenient for assessing the quality of feed in the field [23,95]. Berzaghi et al. [114] in a recent report, compared handheld IR spectrometers to benchtop analyzers. The high accuracy of the results obtained using portable analyzers was noted. Moreover, Acosta et al. [112] did not find a difference in the determination of the component composition of forage hay for millet *Panicum virgatum* L. and Bermuda grass

Cynodon dactylon (L.) when using two portable analyzers in comparison with a stationary spectrometer.

To date, several methods are known for constructing calibration models for processing NIRS data for assessing feed quality. The most common and widely used methods are partial least squares regression (PLS), principal component regression (PCR) [23,117,122], and multiple linear regression (MLR) [102]. In addition, relatively new approaches are the use of machine learning algorithms such as support vector machine (SVM) and Gaussian processes (GP) [123,124]. Specifically, Baath et al. [113] compared SVM and GP machine learning methods with PCR for predicting feed composition for NIRS analysis. The SVM model made it possible to accurately determine the composition of crops *Cyamopsis tetragonoloba* and *Glycine max*. In turn, the SVM and PLS models showed the best results for beans (*Phaseolus acutifolius*) and pigeon peas (*Cajanus cajan*). A combination of NIRS calibration methods can serve as an approach to optimize spectral data processing, eliminating the need for classic feed analysis methods.

Thus, NIRS is an effective analytical method for the rapid and non-invasive analysis of the chemical composition of various types of plant feed. This method is very sensitive, environmentally friendly, and does not require expensive reagents, which makes its use economically beneficial for farms. Currently, NIRS can be used not only to determine the “classic set” of feed components such as moisture, dry matter, crude protein, crude fiber, NDF, and ADF, but also to identify minerals, trace elements, enzymes, and toxins. Hy-perspective probing of pastures makes it possible to assess the species composition of the vegetation cover and to map the area to optimize fertilization. Finally, NIRS probing can be useful in determining the optimal harvest time for forage crops to achieve the maximum energy value of the forage harvested.

5. Future Directions/Prospects for the Development of Optical Technologies for Quality Control on the Farm

The analysis of literature has shown that IR spectroscopy is a convenient method of analysis for agricultural applications. A compact IR spectrometer is a promising tool in production; however, for its accurate and fast operation, it is necessary to develop and improve chemometric algorithms for processing spectral data. The use of the analyzers in real time also does not seem possible without modern data processing algorithms and high-performance capacities. Another direction for the development of optical analysis systems in production is the synchronization of automated processes. In particular, a promising approach is the synchronization of data on significant changes in the composition of milk obtained from an individual animal and data on the composition of its diet. Moreover, the synchronization of the milking process and the analysis of milk can be useful for the detection of markers of cattle pathologies in milk, and, as a result, the rapid cessation of milk production for a given animal. It is important to note the prospects of using portable infrared analyzers, mainly NIRS, in the field, in particular, for assessing the state of pastures and the growth of forage crops. The use of such analyzers in conjunction with unmanned aerial vehicles with subsequent mapping of the terrain will optimize farm costs for irrigation and fertilization. Thus, the improvement of automated optical analysis systems, mainly IR spectrometry, is an economically demanded solution for both small farms and large industrial complexes. Creation of “smart farms”, which implies the automation and synchronization of the diagnostic processes, feeding, and milking of the animal on the farm. This approach significantly improves the quality of life of animals on the farm, which is a key factor in obtaining high quality products and, as a result, the high profitability of this agricultural production.

6. Conclusions

Today, optical methods are accurate, fast, and non-destructive analytical instruments that can be considered as a good alternative to traditional chemical analysis. Numerous studies accumulated over the past decades demonstrate the possibility of using spectral methods to analyze a wide range of components of agricultural products, including those of

both plant and animal origin. Currently, there is a large number of analyzers that allow one to accurately determine the composition of the object under study, both during sampling and in flow mode.

One of the main promising directions in the development of spectral analysis systems is the integration of IR analyzers into automated quality control systems. This approach can be a useful solution for the timely detection of pathologies of animals, improving the quality of products and optimizing the production process as a whole. An important element in optimizing the production process on the farm is to control the quality of feed for farm animals. Fast and automated analysis of feed used in production reduces the economic costs of keeping animals. Such automation on the farm is of great interest, since it allows for the synchronizing of the process of feeding the animal and obtaining high quality dairy products with a known composition. The increase in productivity and the reduction in the cost of computing power, observed recently, allow for the processing of large amounts of data at a relatively high speed. Thus, the creation of new and the improvement of existing chemometric mathematical models make it possible to achieve the high accuracy and speed of the processing of IR spectroscopy data.

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