Mobile Near-Infrared Sensing - A Systematic Review on Devices, Data, Modeling and Applications

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Mobile near-infrared sensing is becoming an increasingly important method in many research and industrial areas. To help consolidate progress in this area, we use the PRISMA guidelines to conduct a systematic review of mobile near-infrared sensing, including 1) existing prototypes and commercial products; 2) data collection techniques; 3) machine learning methods; 4) relevant application areas. Our work measures historical and current trends, and identifies current challenges and future directions for this emerging topic.

CCS Concepts: • **Human-centered computing** → **Ubiquitous and mobile computing**; • **Computing methodologies** → **Machine learning**; • **Applied computing** → *Physical sciences and engineering*.

Additional Key Words and Phrases: mobile computing, near-infrared, mobile sensing, data, machine learning

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1 INTRODUCTION

There are an increasing number of technologies that involve near-infrared (NIR) light. Compared to other electromagnetic (EM) radiations such as ultraviolet (UV) and visible (VIS) lights, NIR light is invisible to the human eye and safe to the human body, and can be either penetrative or sensitive to different materials at different wavelengths [143]. This makes NIR light ideal for many applications that involve material or physiological sensing. In favor of its safety and versatility, researchers have devoted to developing NIR technologies that are more sensitive, requiring less power, with smaller size and lower cost, and ultimately mobile.

With the emergence of mobile devices, there is a paradigm shift for NIR technologies. Conventionally, many NIR technologies are limited to laboratory use. It is mostly mandatory to conduct professional training for using the equipment with thorough operational and maintenance protocols. Such constraints are being eased with the development of more accessible user interfaces (UIs), automated data processing, and simplified instructions [138], in particular for mobile NIR devices. As a result, this paradigm shift brings more opportunities, such as out-of-laboratory applications, as well challenges, such as *in situ* data collection and processing [138].

In this survey, we focus on mobile NIR technologies and their applications, particularly in computer science and related areas. We frame our survey with the following research questions (RQs). We also show an overview of this survey in Fig. 1.

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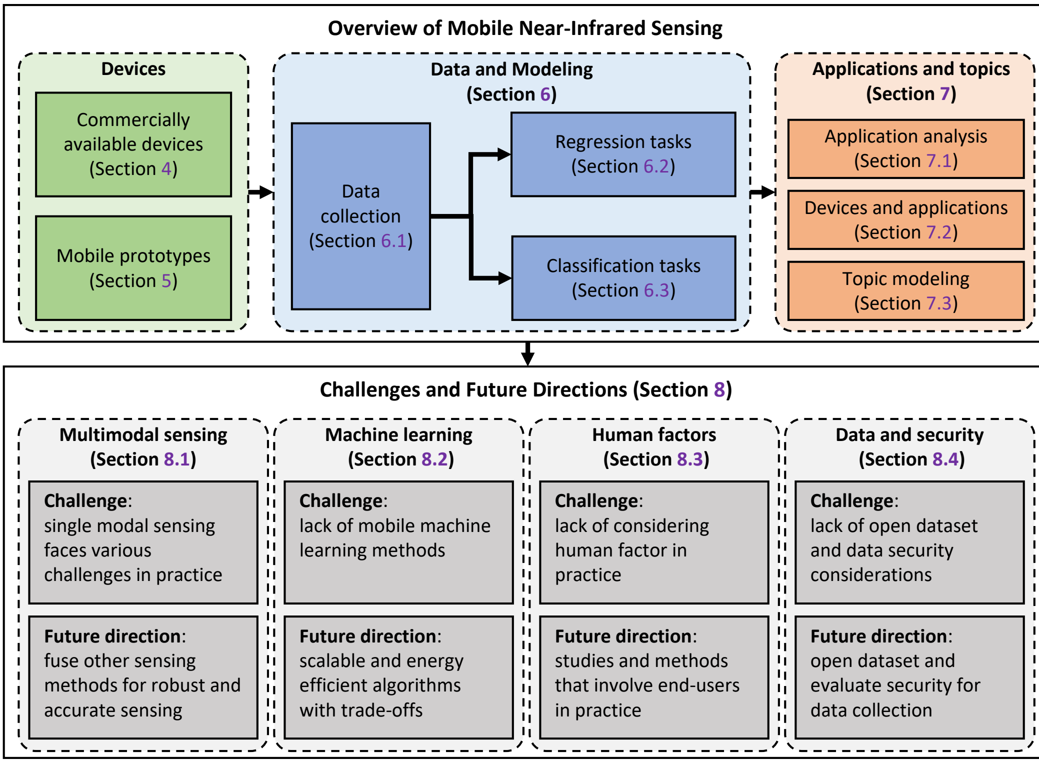

Fig. 1. Overview of mobile near-infrared sensing and article organization.

RQ1: What and how mobile NIR devices are being used or developed? (Section 4 and 5)
RQ2: What kind of data can be collected using mobile NIR devices? (Section 6.1)
RQ3: How to use the data collected by mobile NIR technologies? (Section 6.2 and 6.3)
RQ4: What is the overall trend in mobile NIR technologies – including both the technology and applications? (Section 7)
RQ5: What are the main challenges and opportunities for mobile NIR technologies? (Section 8)

2 BACKGROUND

2.1 Mobile near-infrared methods

Near-infrared (NIR) is a category of invisible light with a wavelength between 700 nm and 2500 nm (Astronomy division [61]). NIR light can typically penetrate objects further than other lights such as ultraviolet (UV), visible (VIS) and even mid-infrared (MIR), while being safe to the human body [143]. Furthermore, many NIR devices are low-cost, small-sized with low power consumption, making them superior for mobile applications compared to alternative methods. To this end, near-infrared has been widely used for many mobile scenarios in research, industry, and daily life.

There are various NIR sensing methods available to achieve different tasks. In general, an NIR method aims to retrieve data after the NIR light interacts with the sensing object, such as diffuse reflection on the object's surface, transmission or penetration through the object, or both. A more complex technique can involve multiple wavelengths of NIR lights, continuous sensing in a period of time, or sensing multiple locations. To date, the most common methods include near-infrared spectroscopy (NIRS), functional near-infrared spectroscopy (fNIRS), and NIR imaging, as illustrated in Fig. 2 and summarized as follows.

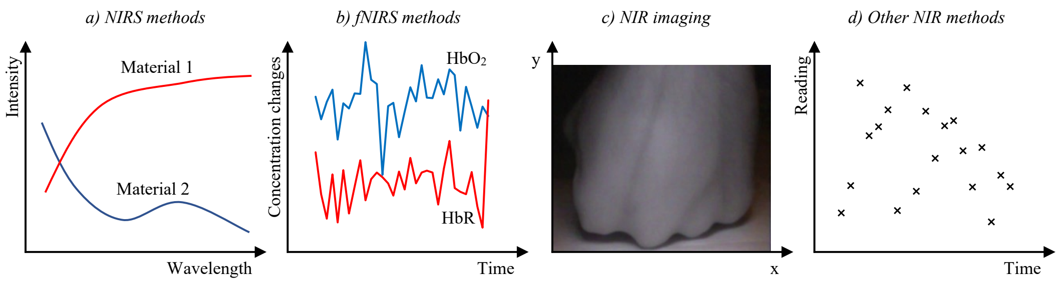

Fig. 2. Illustrations of NIR sensing methods, including: a) NIRS, b) fNIRS, c) NIR imaging, and d) other methods in general. The NIR hand vein image is sampled from an open-sourced dataset [159].

Near-infrared spectroscopy (NIRS) – NIRS utilizes multiple wavelengths of NIR lights to retrieve the material information of an object, especially its chemical components [22]. As particular wavelengths may have different responses to different materials (*e.g.,* reflectance or absorbance), the resulting NIRS spectra are different for distinct materials (illustrated in Fig. 2a). Furthermore, NIRS does not require complex sample preparation and only takes several seconds to scan a sample. Hence, NIRS is superior for mobile material sensing tasks, such as identifying food compositions, water quality analysis, and crop disease detection (Section 4.1 and 5.1).

Functional near-infrared spectroscopy (fNIRS) – While NIRS only focuses on spectral sensing, the fNIRS method can be considered as an expansion and a dedicated use case of NIRS – it focuses on sensing hemodynamics of the human brain, particularly oxygen in the blood, represented by concentration changes of oxygenated hemoglobin (HbO_2) and deoxygenated hemoglobin (HbR). For that, typical fNIRS utilizes NIR at two wavelengths – ~760 nm for sensing HbR and ~850 nm for sensing HbO_2 respectively [188]. Since both wavelengths are relatively translucent to human tissue, but can be absorbed by HbR (at ~760 nm) or HbO_2 (at ~850 nm). Such features make fNIRS superior for sensing the hemodynamics of the human brain. Furthermore, many fNIRS devices also monitor the human brain at different locations (*i.e.,* channels) at the same time, resulting in dynamic imaging of the brain activity for analyzing different brain areas. We illustrate the fNIRS signals in Fig. 2b for one channel. Finally, compared to other brain imaging methods, fNIRS is relatively low-cost and can be mobile (compared with functional magnetic resonance imaging or fMRI), with better usability and lower noise (compared with electroencephalography or EEG) [90]. Also, fNIRS is still under active engineering that may be improved in the near future (Section 5.2).

Near-infrared imaging – Besides NIRS and fNIRS, near-infrared imaging is also a typical sensing method that utilizes near-infrared. Fundamentally, NIR imaging expands the human eye's perception beyond visible (VIS) light, yielding extra information that cannot be seen. Also, as near-infrared can penetrate many objects in a moderate depth (up to several centimeters [85]), the imaging outcome can include information inside the object, such as biometric features (*e.g.,* iris, hand veins as illustrated in Fig. 2c). Furthermore, near-infrared fluorescence imaging is also commonly adopted for highlighting specific objects, using targeted NIR fluorescent agent that attaches to pre-designated tissues (*e.g.,* human cancer cells) [96]. Recent studies also include mobile scenarios in healthcare, authentication, and human–computer interaction (HCI) (Section 5.3).

Other near-infrared methods – Finally, there are also other near-infrared sensing methods for mobile scenarios. For example, photoplethysmography (PPG) is mostly used for the pulse oximeter to measure blood volume changes [111], while photoglottography (PGG) is used for sensing glottis in the larynx [32]. For particular applications, there can be a distinctive sensing technique applied using near-infrared (Section 5.4).

Table 1. A comparison of recent surveys focusing on NIR sensing methods and their scope.

Survey	**Near-infrared methods**				**Mobile scenario?**	**Scope**			
	NIRS	fNIRS	Imaging	Other		Device	Application	Dataset	Modeling
[74]	✗	✓	✗	✗	✗	✓	✓	✗	✓
[70]	✗	✓	✗	✗	✗	✓	✓ depression	✓	✗
[27]	✗	✓	✗	✗	✗	✓	✓ neuro-science	✗	✗
[160]	✗	✓ fNIRS-EEG	✗	✗	✓ wearable	✓	✗	✗	✗
[73]	✗	✗	✓ fluorescence	✗	✗	✓	✓ biomedical	✗	✗
[45]	✗	✗	✓ photoacoustic	✗	✗	✓	✓	✗	✗
[35]	✓ VIS & NIR	✗	✗	✗	✗	✓	✓ agriculture	✗	✓
[25]	✓	✗	✓ hyperspectral	✗	✗	✓	✓ food	✗	✓
[14]	✓	✗	✗	✗	✓ miniaturized	✓	✓	✗	✗
[15]	✓	✗	✗	✗	✓ miniaturized	✓	✓ agriculture and food	✓	✓
Ours	✓	✓	✓	✓	✓	✓	✓	✓	✓

2.2 Related surveys

There are a number of surveys focusing on NIR sensing methods with various aspects. However, existing surveys have different scopes that either limit specific sensing methods or a particular application area. For example, Hong and Yaqub reviewed recent studies on fNIRS while focusing on the healthcare industry [74]. Also, Ho et al. and Chen et al. present reviews of using fNIRS for diagnosing major depression disorder [70] and neuroscience [27] respectively. Furthermore, Uchitel et al. reviewed recent studies on wearable fNIRS-EEG methods, focusing on the devices such as new prototypes [160]. Besides, fNIRS, Hong et al. and Du et al. show reviews of NIR imaging, focusing on fluorescence [73] and photoacoustic [45] respectively. Finally, existing surveys also include the NIRS method. For instance, Cortés et al. and Chandrasekaran et al. reviewed studies using NIRS for quality control in agriculture [35] and fruits [25] respectively. In addition, Beć et al. highlight in their review the emerging miniaturized NIRS method that is mobile and useful for agriculture and food [14] and other fields [15].

In this survey, we focus on mobile near-infrared (NIR) sensing methods including NIRS, fNIRS, NIR imaging, and other sensing methods. We also show analysis results regarding 1) mobile devices including both commercial products and prototypes, 2) applications in different areas, 3) datasets that were generated in recent studies, and 4) modeling methods, in particular machine learning, to achieve different tasks using mobile NIR sensing methods. We show the differences between related surveys and our survey in Table 1.

In addition, based on the survey results, we discuss challenges and future directions in the mobile near-infrared study field, including open datasets, machine learning methods for mobile devices, and human factors that may affect the performance of mobile near-infrared methods. Furthermore, while security is not a main research topic in this area, we note the lack of consideration for data security, which can be crucial for in-the-wild use cases in the foreseeable future.

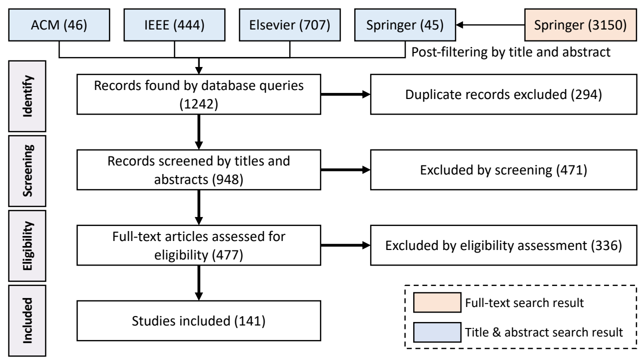

Fig. 3. Study selection using the four-phrase PRISMA guidelines.

3 METHODOLOGY

This review follows the Preferred Reporting Items for Systematic reviews and Meta-Analysis (PRISMA) four-phase guideline [134]. First, we identified study records using a search strategy to query publication databases (Section 3.1). Second, we screened the search results by title and abstract to exclude out-of-scope records. Third, full-text articles were assessed based on the eligibility criteria (Section 3.2). Finally, eligible studies were included in this review for analysis.

3.1 Search strategy

The initial search was performed based on the topic of this review to include the most relevant studies. Considering the two main parts of the topic – mobile and near-infrared – the query statement was defined below

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(mobile OR portable OR wearable OR handheld OR miniatur*)
AND ((near AND infrared*) OR NIR*)
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where the asterisk symbol $*$ represents as arbitrary non-space characters. The query was performed for the titles and the abstracts respectively. Four primary databases were included – ACM Digital Library, IEEE Xplore, Springer Link, and Elsevier Scopus (which contains Science Direct). Also, to include the most relevant studies, both Springer and Elseviers' databases were limited to conference papers or journal articles in computer science. Finally, the publication dates were limited to between 2012 and 2022 to include recent studies.

We note that since Springer Link did not provide the option to limit the search to titles or abstracts[1], we had to follow a slightly different process to identify the papers. First, we did a full-text search in Springer Link and downloaded the results. Next, we filtered the results using a Structured Query Language (SQL) statement. The SQL statement is defined as identical to what we used for other databases (*i.e.,* ACM, IEEE, and Elsevier).

3.2 Study selection

In total, 1242 query results were returned from the databases (46 from ACM, 444 from IEEE, 45 from Springer[2], and 707 from Elsevier). After removing duplicates by title, 948 studies were initially included for screening and eligibility assessment. The studies were selected with the criteria below:

Criterion 1 – publication category: The study must be published as a peer-reviewed technical paper. Publications such as progress reports, opinion papers or theses are excluded.

[1]This limitation may only exist at the time point of submission.
[2]Initially, 3150 results returned from the full-text search, 45 results remained after post-filtering by title and abstract.

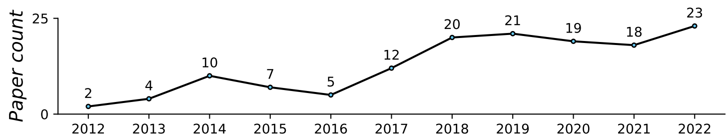

Fig. 4. Numbers of papers published by year between 2012 and 2022.

Criterion 2 – involve near-infrared: The study must involve near-infrared. Studies using only other technologies such as ultra-violet, visible light, or thermal imaging that uses mid-far infrared light are excluded.

Criterion 3 – mobile device: The study must involve a mobile device. Studies that depend on a setup that cannot be readily moved, such as devices that are implantable, must run with a local personal computer (*e.g.,* controlling a device over USB), or must be connected to grid power, are excluded.

The whole study process is illustrated in Fig. 3. Overall, 471 studies were excluded by title and abstract screening, and 336 studies were excluded by full-text eligibility assessment. In total, 141 studies were included in this review for the analysis.

4 COMMERCIALLY AVAILABLE MOBILE NEAR-INFRARED DEVICES

In this survey, we first analyze mobile near-infrared devices that are used in the literature. Unlike fields that focus on theoretical or algorithmic studies, the device is one of the fundamental requirements to conduct studies that involve mobile near-infrared. In many cases, using a different mobile near-infrared device impacts the results of targeted studies. As an example of another mobile sensing field, the Wi-Fi channel state information (CSI) sensing method leverages standardized Wi-Fi devices [114]. Since all devices comply with the same protocol (*i.e.,* IEEE 802.11), most Wi-Fi sensing studies can be generalized to common Wi-Fi devices.

In contrast, mobile near-infrared devices are still under active engineering, we are yet to have a standardized protocol like Wi-Fi does. Although particular areas such as medical devices (*e.g.,* oximeter and fNIRS) have specific standards, they are not necessarily comprehensive nor compulsory worldwide. One main reason is that, unlike Wi-Fi which serves a universal purpose (*i.e.,* wireless connectivity), mobile near-infrared devices must adapt to diverse use cases or scenarios, making their standardization much more complex. For example, while most fNIRS devices are used for brain imaging, these devices have to be adapted to various biological individual differences (*e.g.,* human subjects at different ages) and distinct applications (*e.g.,* real-time human-brain interfaces that leverage specific brain activities, or cognitive studies that require high-resolution imaging).

Nevertheless, there are still some mobile near-infrared devices that are commercially available for a broad range of use cases, as detailed in this section. The most common products include NIRS scanners for spectral analysis and fNIRS systems for monitoring hemodynamic activities or neural imaging. Other mobile near-infrared sensing products are still quite limited. In particular, the availability of suitable, off-the-shelf mobile near-infrared imaging devices is quite limited, especially when considering the feasibility of a wide range of applications. Hence, the limited availability and relatively high cost motivate researchers to develop custom near-infrared imaging systems tailored to specific application scenarios. These systems often provide improved adaptability and performance for particular use cases.

Similarly, researchers also strive to develop other mobile sensing methods, including NIRS and fNIRS, beyond using commercial products. However, developing a mobile sensing device requires specialized skills with more considerations, as detailed in Section 5, where we explore the motivations and challenges behind the development of these custom near-infrared prototypes.

4.1 Commercial mobile NIRS products

In this section, we provide a comprehensive comparison and analysis of the commercially available mobile NIRS products that have been used by recent studies, as shown in Table 2. In particular, for mobile scenarios, we outline the following main features for consideration and then provide examples for different use cases. We then summarize the advantages and disadvantages of these devices, including their main use cases and limitations, primarily categorized by their wavelength ranges which are the fundamental features of NIRS devices.

- *Wavelengths* – the wavelength range the device covers. In principle, a NIRS device with a wider wavelength range can be used to detect more types of components (detailed below for each product respectively). It is worth noting that, as the spectrum of NIRS usually spreads in multiple wavelength bands, a higher digital resolution is not the primary consideration in most use cases (digital resolution – the number of distinct wavelengths within the range). Further, some devices that also include VIS spectrum or UV spectrum can cover more application scenarios.
- *Connectivity* – how the device connects to other devices for data transfer. The most common methods include local storage (*e.g.,* internal storage or secure digital (SD) cards), universal serial bus (USB), Bluetooth, and WiFi. Other connectivity methods are not included for their infrequent use in mobile scenarios (*e.g.,* Ethernet).
- *UI and apps* – the user interface and its corresponding software for interacting with the device. A mobile NIR device typically has an onboard screen (*i.e.,* standalone mode), or a mobile app (*e.g.,* Android, iOS, or other mobile devices), or a desktop software.
- *Battery* – for how long or how many scans the battery can last. Although some devices do not have an internal battery or battery slot, they can be readily powered up with an external power band via USB.

Devices with narrow wavelength range. Devices like *SPAD 502DL Plus*, limited in wavelengths, are specialized for tasks such as chlorophyll analysis in leaves [16, 164]. Studies with these devices find that while their narrow focus enables precision in specific scenarios, they can only provide a limited analysis in broader applications, such as sensing water or nutritional content. Similarly, devices like *SpectraVista GER 1500* and *FieldSpec HandHeld* are useful in remote sensing and *in situ* analysis [16, 147, 164], but are limited to scenarios that fall within their wavelength range.

Devices with wide wavelength range. In contrast, devices like *AB Vista NIR4*, *InnoSpectra NIR*, and *TI NIRScan Nano*, covering wider wavelength ranges, offer greater versatility across various applications [13, 24, 62, 170, 176]. These devices are found adaptable to a broad range of scenarios, including the aforementioned leaf analysis and remote sensing scenarios using devices with narrower wavelengths, and other applications such as forage analysis and chemical composition estimation. Furthermore, there are devices with extended wavelengths up to 2500 *nm*, such as *microPHAZIR* and *Si-Ware NeoSpectra* can be catered to specialized applications like berry cell vitality assessment or soil content analysis [5, 8, 38, 56, 119]. These devices capture a wider spectrum of information, beneficial for detailed analyses in specific fields. However, while these devices are mostly designed for general purposes, they may be more expensive or need further procedure such as data processing as detailed in Section 6.

Key comparisons between devices with narrow- and wide- wavelengths. The evolution of NIR devices has been driven by diverse application needs, leading to parallel developments in both narrow and wide-wavelength devices. While wide wavelength devices offer comprehensive analysis capabilities, narrow wavelength devices continue to be developed for their specific advantages in cost, simplicity, and targeted application accuracy. This understanding is vital for future research and development in NIR technology.

Table 2. A comparison of commercially available mobile NIRS products used by recent studies.

Products	Wavelengths	Connectivity				UI & Apps			Battery	References
		💾	USB	ᛒ	📶	⏵	📱	🖥		
AB Vista NIR4	950 - 1750 nm	✓			✓	✓			N/A	[31]
FieldSpec HandHeld	325 - 1075 nm	✓	✓			✓		✓	2.5 h	[16, 52, 86, 99, 127, 144, 153, 164]
InnoSpectra NIR Series	900 - 1700 nm		✓	✓			✓	✓	N/A	[13, 170, 176]
LinkSquare	440 - 1000 nm				✓		✓	✓	1000 scans	[124, 182–184]
microPHAZIR	1595 - 2400 nm	✓	✓			✓			5 h	[8, 38, 56, 119]
PSR+ 3500	350 - 2500 nm	✓	✓	✓			✓	✓	4 h	[148]
RCI Aurora NIR	950 - 1650 nm	✓	✓	✓	✓	✓		✓	2-8 h	[13, 31]
SCiO Series	740 - 1050 nm		✓	✓			✓		300 scans	[13, 31, 101, 126, 155]
Si-Ware NeoSpectra	1350 - 2500 nm			✓			✓		800 scans	[5]
SPAD 502DL Plus	650 nm, 940 nm	✓	✓			✓		✓	40 h	[16, 164]
SpectraVista GER 1500	350 - 1050 nm	✓		✓		✓	✓		4 h	[147]
StellarNet BLACK-C-SR	200 - 1080 nm		✓		✓		✓	✓	N/A	[98]
TI NIRScan Nano	900 - 1700 nm	✓	✓	✓			✓	✓	N/A	[24, 62]
Unispec-SC	310 - 1100 nm		✓			✓			4-6 h	[136]

💾 The device can run in standalone mode with local storage.
USB The device can be connected via USB.
ᛒ The device can be connected via Bluetooth.
📶 The device can be connected via WiFi.
⏵ The device has an onboard user interface (*i.e.*, an onboard screen).
📱 The device can be operated using a mobile app.
🖥 The device can be operated using a desktop application with GUI.

Notes on commercial mobile NIRS devices. Finally, we emphasize that for mobile scenarios, connectivity and UI are crucial for usability. Devices with wireless connections and mobile apps offer ease of use for *in situ* analysis and potential for future applications. Researchers and developers should consider devices demonstrated to be effective in their targeted use cases, with suitable connectivity options, and those offering a wider wavelength range for greater versatility.

4.2 Commercial mobile fNIRS products

From the technology perspective, the fNIRS method can be considered as a specialized NIRS method. However, rather than focusing on the responses in a range of wavelengths, it concerns the signal changes in time for multiple channels (measurement locations). As clarified before, a typical application of fNIRS is to monitor brain activities through cerebral oxygen changes – in particular the concentrations of oxygenated hemoglobin and deoxygenated hemoglobin [188]. This makes most fNIRS devices utilize two wavelengths (~760 nm and ~850 nm) with multiple probes (channels) to measure different locations in time.

Similar to NIRS, using a commercial product is the primary choice for conducting studies that involve mobile fNIRS. Nevertheless, as most commercial fNIRS devices are designed for the aforementioned brain activity monitoring, there are fewer distinctions among the devices. Here, we show a comparison of mobile fNIRS devices used in recent studies (Table 3). Besides the features for NIRS, we also consider the number of channels (#Ch) as a main feature for fNIRS.

Table 3. A comparison of commercially available mobile fNIRS products used by recent studies.

Products	Wavelengths (nm)	#Ch	Connectivity				UI & Apps			Battery	References
Artinis Medical Systems	760, 850	up to 54	✓		✓				✓	3 h	[20, 44, 108, 115, 189]
Hitachi WOT-100	705, 830	16 - 22	✓			✓			✓	2-2.5 h	[68, 157]
Hitachi WOT-220	705, 830	22	✓			✓			✓	2-2.5 h	[128, 133]
NIRSIT Series	780, 850	up to 48		✓		✓		✓	✓	8 h	[87, 150, 156]
NIRx NIRSport 2	760, 850	45 - 55	✓	✓		✓			✓	5-6 h	[89, 166]
NeU HOT-1000	800	2			✓			✓		1.5 h	[129, 141, 177]
NeU HOT-2000	800	2			✓			✓		4 h	[129]
PLUX Wireless Biosignals	660, 860	4 - 8		✓	✓				✓	10-20 h	[162]
Pocket NIRS Duo	735, 810, 850	2			✓			✓		N/A	[107, 117]
SenSmart X-100	unspecified	4	✓		✓		✓			1-3 h	[149]

Devices with limited channels. Previous studies find that fNIRS devices with a relatively small number of channels (less than 10) can only be used in limited applications requiring coarse hemodynamic activity. Examples include *NeU HOT-1000*, *NeU HOT-2000*, *Pocket NIRS Duo*, and *SenSmart X-100*, which have only 2, 2, 2, and 4 channels, respectively. Recent studies utilizing these devices are typically centered around high-level, abstract, or straightforward tasks. For instance, Yamamura et al. used *HOT-1000* to estimate cybersickness in VR for adjusting the user's field of view, a strategy that can potentially minimize the user's cybersickness [177]. Furthermore, Varandas et al. and [107] show that *PLUX Wireless Biosignals* and *Pocket NIRS Duo* can be adopted in detecting cognitive fatigue [162] and muscle fatigue [107], respectively.

Devices with numerous channels. In contrast, previous studies find that fNIRS products with an expanded channel capacity (*i.e.,* tens of channels) can be adopted in both simple and complex tasks. For example, *WOT-100* and *WOT-220* are frequently employed to monitor brain activity during various cognitive tasks, including estimating the index of visual fatigue during reading tasks [157], analyzing acting performance [68], and investigating effects of computer games on brain activity [133]. Also, the *'Brite' Artinis* series shows uses case in classification tasks and analysis of brain activity in dynamic situations, including classifying cognitive event onsets in three cognitive tasks (simple arithmetic, 1-back, and 2-back memory) [44], investigating transcutaneous photon transmission for measuring pigmented subjects [20], correlations between brain activity during sleeping and stress [108], investigating memory-related prefrontal cortex activity in the elderly with diabetes [189], and even classifying breathing conditions (baseline, loaded, rapid) [115].

Similarly, other devices with a relatively more number of channels show high capability in various tasks, such as analyzing brain activity in motion, including walking for neurologically injured patients (*NIRSIT Obelab*) [87], basketball dribbling [89] and fine-grained brain's microstates during surgical tasks [166] (*NIRx NIRSport 2*). Such devices can also be adopted in monitoring brain activities during driving such as analyzing brain activity during driving in winter [150] and before and after take-over request in automated driving [156] (*NIRSIT LITE*).

Notes on commercial mobile fNIRS devices. Overall, previous studies indicate that the main limitation for fNIRS is the number of channels. In particular, complex tasks require detailed brain imaging that cannot be fulfilled by devices with limited channels. However, in general, fNIRS devices with more channels are usually more expensive. They thus may not be feasible for all scenarios[3]. Also, for in-the-wild studies, it can be crucial to include wireless connectivity with

[3]We are unable to provide reference prices as many of them are not publicly available.

mobile apps. Referring to the details above and Table 3, as a common guideline for researchers and developers with limited budgets, it is recommended to choose the mobile fNIRS device that can accomplish the targeted tasks with a minimal number of channels. With multiple choices, a device with wireless connectivity and mobile apps would be preferred.

5 MOBILE NEAR-INFRARED PROTOTYPES

Despite the availability of commercial products, certain scenarios still require customization or development of mobile NIR devices. In particular, as many use cases of mobile NIR devices are highly correlated to the measurement targets, specific features must be adapted. For example, a common use case of NIRS is to analyze the chemical compositions of an object (*e.g.,* sugar contents in fruit or juice). While the objects can have distinct shapes (*e.g.,* sphere-like, powder) or even different states of matter (*e.g.,* liquid, solid). To achieve optimal performance, the devices must be adapted to the corresponding objects to acquire higher SNR NIR spectra.

Also, for fNIRS, albeit the availability of commercial devices, there are also particular requirements that need to be addressed through prototyping. For example, many studies aim to improve the usability of mobile fNIRS. A main advantage of mobile devices is that the activity of users would not be constrained to a designated area, compared to desktop ones. Thus, the usability of mobile fNIRS is a significant factor to be considered (*e.g.,* whether it can be worn by the user comfortably). There are also other motivations for prototyping mobile fNIRS devices such as improving the SNR of the signals, or combining with other methods such as BMI for multimodal sensing.

In this section, we show an overall of mobile NIR prototypes. In particular, we group the prototypes by the underlying technologies into NIRS (Section 5.1), fNIRS (Section 5.2), NIR imaging (Section 5.3), and other NIR sensing prototypes (Section 5.4).

5.1 NIRS prototypes

We summarize recent studies that involve developing mobile NIRS devices in Appendix Table 1 (sorted by use cases). Besides wavelengths, connectivity and UI, we also include a "computing" feature showing the onboard computing unit used for the prototype. Furthermore, we find the main motivations for prototyping instead of using a commercial product as 1) *modality and usability*, 2) *cost*, and 3) *novel sensing method.*

Modality and usability. Depending on practical use cases, the modality of the NIRS scanners should vary for optimal performance and usability (*e.g.,* liquid, solids, human body). However, it is infeasible for a commercial product to maintain an exhaustive list of modalities. For example, to analyze liquids, Jiang et al. designed a 3D printable clamp NIRS device that can be easily used in everyday scenarios [82]. Also, Aira et al. prototyped SpectroGLY for analyzing glyphosate residues in water [3], with a mobile app for *in situ* analysis and a web-based interface for remote access. Moreover, researchers designed different modalities for NIRS devices for analyzing milk [125, 178]. Likewise, a commercial NIRS device can be used for analyzing forage quality in a dairy farm (*e.g.,* [13, 31]). However, as the sample is not homogeneous (*i.e.,* scanning different locations result in different spectra), users have to scan multiple spots to acquire an optimal result. Alternatively, an automatic method is to attach a servomotor to stir-then-scan the samples [51, 142]. Other modalities are designed for various applications, such as soil analysis [46, 191], estimating blood gluten [185], assessing sleep apnea [12], identifying pharmaceuticals [28, 93], detecting gluten in breads [83], estimating mango maturity [92], and predicting moisture content in C. oleifera seeds [139].

Reducing cost. For particular applications, specific features are required. Notably, some wavelengths can be more effective in those applications. A common commercial NIRS product may not cover those wavelengths – users may require another high-end or dedicated device that is usually expensive. On the other hand, a commercial device may include extra wavelengths that are unnecessary. In addition, some products may require extra payment for subscription to their software or additional features (*e.g., SCiO*), which may be infeasible in the long term.

To this end, researchers have developed mobile NIRS devices that are low-cost yet effective in the targeted use cases. For example, Chowdhury et al. reported that the wavelengths between 870 nm and 1000 nm are the most suitable for glucose detection (peaked at 963 nm), while a narrow band peaked at 845 nm is more suitable for insulin detection [33]. The authors then developed a low-cost device based on these wavelengths to detect glucose and insulin in the blood. Other studies also reported similar methods with different wavelengths, including detecting glucose in blood [54, 161], monitoring blood oxygen [23, 37], leaf nitrogen [186] and water [67], and assisting early diagnosis of breast cancer [50].

Novel sensing methods. Moreover, researchers also developed prototypes for novel sensing methods using NIRS. For example, Fouad et al. presented a multimodal sensing method using both NIRS and bio-impedance spectroscopy (BIS) [54] for monitoring glucose in the blood, achieving better accuracy compared to NIRS on its own. Further, Jahagirdar and Sharma developed a prototype to infer glucose in the blood from saliva [54]. In addition, as an example of everyday use cases, Balakit et al. developed a method to detect the ripeness of watermelon by combining acoustic analysis and NIR spectra, achieving a higher accuracy compared to using only one of the signals [10]. Also, Hu et al. developed a smartphone attachment with multiple NIR light sources. The authors successfully estimated food calories using normal photos and NIR spectra [75].

Notes on NIRS prototypes. In short, researchers developed different mobile NIRS devices for improving usability in different scenarios, reducing cost, or presenting a novel sensing method. Compared with adopting a commercial device in a study, prototyping a mobile NIRS device can be significantly more complex. For example, the wavelength is the fundamental factor that affects the performance of NIRS. However, as the underlying principle in physics is not fully revealed, researchers have to rely on previous studies to choose the wavelength span, or conduct necessary experiments to evaluate the performance using selected wavelengths.

Besides wavelengths, it can also be very important to choose other components such as computing units. Commonly available platforms such as Arduino and Raspberry Pi can be readily used, but they also have relatively high energy demand. Alternatively, a less complex way for prototyping a NIRS device is by customizing a commercial product or development kit, such as *TI NIRScan Nano* and *Si-Ware NeoSpectra-Micro*. However, they may have limitations on particular hardware specifications including wavelengths and modalities. Based on the survey result, we would recommend referring to the most related use cases as shown in Appendix Table 1 for prototyping.

5.2 fNIRS prototypes

Beyond NIRS, there are also significant studies that involve fNIRS prototypes. Compared to NIRS, fNIRS devices are mostly used for specific scenarios – monitoring the human brain's activity. Therefore, researchers put more focus on improving different aspects of fNIRS. We summarize mobile fNIRS prototypes developed in recent studies in Appendix Table 2. Furthermore, we highlight the following three main motivations for prototyping mobile fNIRS devices: 1) *improving usability*, 2) *improving performance*, and 3) *novel sensing methods*.

Improving usability. A fundamental problem for a mobile fNIRS device is usability. As users need to wear the device for a certain amount of time which can be up to a whole day, it is very important to make sure the device can be comfortably worn. Also, as most fNIRS devices are still used for scientific studies, it is helpful for the researchers to make the devices readily operated. Hence, researchers have made substantial efforts to improve usability for mobile fNIRS devices. For example, Saikia et al. developed a mobile fNIRS system that is wearable and connected via WiFi, the device can be remotely configured through the Internet, allowing easy operation for the researchers and developers [145]. However, the hardware still requires more development for actual use. In contrast, Watanabe et al. described how PocketNIRS Duo was developed – a commercially available device afterward as mentioned in Section 4.2.

Furthermore, several mobile fNIRS devices were developed that can be comfortably worn by the users. For example, Ha and Yoo showcased an in-ear wearable fNIRS system [66]. Such a design can reduce the device awareness of users during the study. However, limited by the size of the device, it only has 1 fNIRS channel with 1 EEG channel. The device is also dedicated to drowsiness monitoring. Similarly, researchers developed mobile fNIRS devices that are miniaturized [146, 151], headphone-like [188], or 3D-printed for better fitting [2]. Nevertheless, as a hardware limitation, they have a relatively small number of channels (*e.g.,* mostly 2 channels) that can only be used in coarse sensing tasks as described in Section 4.2.

Improving performance. Besides usability, an important issue for mobile fNIRS systems, compared with stationary ones, are signal noises or interference generated by motion. Recent studies show several promising methods to improve both usability and the SNR for fNIRS. For instance, Saikia and Mankodiya added a short channel regression that can eliminate background interference [146]. Alternatively, Siddiquee et al. presented a method to fuse inertial measurement unit (IMU) sensors to remove motion artifacts from fNIRS signals [152]. A more straightforward way, with the advancing of integrated circuit (IC) technology, is to use high-quality bio-optical components with low-noise (*e.g.,* TI ADS8688A [100]). In addition, Yaqub et al. presented a high-density prototype to improve the brain imaging resolution [181].

Novel sensing methods. Beyond usability and data quality, researchers also endeavor to build novel fNIRS systems including multimodal sensing methods and BMI systems. In particular, Guo et al. showed a method that measures muscle activity using both surface electromyography (sEMG) and fNIRS signal [64], and achieved high classification accuracy for gesture recognition, compared with the fNIRS method [180]. Alternatively, Ha and Yoo developed an EEG-fNIRS system for monitoring user's drowsiness [66]. The authors reported 20% classification accuracy improvement over conventional methods (*i.e.,* using EEG or fNIRS only). Likewise, von Lühmann et al. presented a EEG-fNIRS method for hybrid BMI in telemedicine and assistive neurotechnology scenarios [165]. In addition, Chen et al. presented a novel dual-level adaptive sampling technique for mobile fNIRS. By changing the active channel pattern, the authors successfully reduced energy consumption significantly (up to 46.58% for the LED module), without greatly reducing the performance [26].

Notes on fNIRS prototypes. In short, our survey indicates that researchers devoted to improving the usability and performance of mobile fNIRS prototypes, and studied novel sensing methods, particularly multimodal sensing, which combines fNIRS with other physiological sensing techniques to enrich the data collection of human activities in more effective ways. Compared with fNIRS, the underlying sensing hardware can be not as complex, as the required wavelengths are mostly determined (*e.g.,* ~760 nm and ~850 nm). However, mobile fNIRS devices intrinsically involve human subjects that can be challenging to anticipate. Hence, based on the survey results, we note that mobile fNIRS prototypes should take more consideration for user-related issues, which can demand sophisticated solutions in particular scenarios.

5.3 NIR imaging devices

Besides NIRS and fNIRS, the mobile NIR imaging method is also useful in many scenarios. As we summarize in Appendix Table 3, recent studies also include prototyping mobile NIR imaging devices for different use cases. Notably, the main motivation of NIR imaging is to acquire data in space that may be invisible to human eyes. In this survey, we categorize mobile NIR imaging prototypes into *healthcare*, *eye-tracking*, and *other use cases*.

Healthcare. A main use case of mobile NIR imaging is to image the human body to retrieve information under the skin. in healthcare scenarios. For example, a recent study by Chowdhury et al. demonstrated a low-cost implementation of a mobile NIR imaging system for visualizing veins of arms. The system can be used for assisting intravenous (IV) access (*i.e.,* reducing vein puncturing failure rate) [34]. Also, Ern et al. validated a portable NIR imaging system for visualizing dorsal hand veins with different skin tones [49]. Furthermore, Oh et al. developed a handheld NIR imager for thyroid surgery [131]. The device can help localize parathyroid glands to avoid damaging or accidental removal of the parathyroid glands during the surgery [131]. Moreover, mobile NIR imaging devices can also help to detect cancer cells, with different wavelengths and modalities, such as breast cancer cells for early detection using a handheld system [30], or interoperative guidance using a goggle display (i.e., head-mounted display or HMD) [57]. Also, Alam et al. showed a proof-of-concept device for detecting colorectal cancer cells that can be further developed for practical use [4].

Eye-tracking. Beyond healthcare, researchers also presented multiple mobile NIR prototypes for everyday scenarios. For example, NIR has been widely used in eye-tracking devices. In particular, Wang et al. proposed a device for detecting pupil and glint using a NIR LED array and a wearable camera [167]. The device achieved higher accuracy with more robustness compared to conventional methods [167]. Furthermore, Mayberry et al. presented a computational eyeglass integrating a NIR illumination. The authors further developed an indoor-outdoor switching algorithm to optimize power consumption [118]. A more recent study by Li and Zhou demonstrated an even lower power eye-tracking glasses that is battery-free. The authors proposed a camera-less design using NIR LEDs and sensors, with a lightweight inference algorithm and an energy harvesting unit [106].

Other use cases. Besides eye-tracking, mobile NIR prototypes are also developed for other use cases, including security, gesture recognition, and localization. For example, Hickman developed a handheld multi-band fusion camera that can be used for security and surveillance in various contexts. The authors customized a longwave infrared (LWIR) camera (*i.e.,* mid-far infrared) by adding secondary sensors for both VIS and NIR imaging [69]. A more common security-related application for NIR imaging is biometric recognition. For instance, Debiasi et al. prototyped a smartphone peripheral with NIR LEDs and a NIR-pass filter. Using the corresponding mobile app, the authors succeeded in authenticating users using their vascular patterns (*i.e.,* hand veins) [39]. A follow-up study by Garcia-Martin and Sanchez-Reillo showed that the same tasks could be achieved using particular Android phones without hardware modifications, with a customized app and rooted privilege (*i.e.,* a process to gain superuser permission for low-level system access) [58]. Finally, researchers also developed mobile NIR devices for gesture recognition with lower power consumption [174], a multi-sensor system for localizing bats that is mobile compared to conventional methods [71], a mobile phone attachment for imaging embedded tags in 3D prints using NIR translucent materials [43], a multi-spectral camera for analyzing conservation and restoration of paper-based artifacts [158] or predicting biochemical variables of grape berries [36], respectively.

Notes on NIR image prototypes. If we consider NIR imaging as an extension of NIRS with an additional dimension, both techniques can be an alternative to each other for retrieving information that is invisible to the human eyes. For NIRS, users can acquire more detailed information in multiple wavelengths, while for NIR imaging, users can acquire more detailed information in space. Albeit hyperspectral imaging can achieve both, they are still very expensive and challenging to prototype for mobile scenarios [85]. Nevertheless, our survey result indicates various use cases of mobile NIR imaging prototypes can be further studied in the future.

5.4 Other NIR prototypes

Finally, we identify other mobile NIR devices that can be used in various scenarios, as summarized in Appendix Table 4. It is worth noting that, based on our best knowledge, we re-categorize several studies ([55, 116, 122]) to general NIR sensing methods, albeit the authors classified their prototypes as NIRS, while the prototypes do not involve spectral sensing methods.

As highlighted above, the strengths of NIR methods (*i.e.,* NIRS, fNIRS and NIR imaging) are particularly in the field of healthcare as recent studies have focused on. For instance, the device developed by Molavi et al. provided a solution for bladder monitoring for patients with neurogenic conditions, with the strength of activating an alarm when the bladder is full [122]. Researchers also innovated blood glucose monitoring systems that are cost-effective [81, 116], have improved SNR[97], or are able to provide insulin dose recommendation[21]. Furthermore, based on the photoplethysmography (PPG) technique, researchers presented wearable prototypes for monitoring blood oxygen and pulse measurement for remote users [55], or continuous blood pressure estimation [111]. Compared to alternative techniques, the main advantage of those devices is the measurements can be taken in a non-invasive manner in real-time. However, the measurements can be less accurate compared to the invasive ways (*e.g.,* invasive blood glucose measurement is still considered the golden standard).

Moreover, researchers demonstrated the versatility and strength using mobile NIR sensing prototypes, such as measuring interaction proxemics in social activities [123], monitoring vocal fold vibration [32], detecting tea polyphenols [171], and measuring optically equivalent grain size of snow [60]. Nevertheless, it should be noted that these methods come with their own set of constraints, as they are often scenario-specific and their performance may not be generalized across different contexts or use cases.

Finally, there are specific NIR sensing techniques that, while limited in number, present unique strengths in their respective application domains. For example, Rahman et al. utilized photoacoustics in near-infrared for characterizing liquid food [140]. Also, Joshi et al. adopted near-infrared for phototherapy for hyper-pigmentation [88]. Furthermore, Gurulian et al. demonstrated that in the contactless transaction scenario (*e.g.,* NFC payment), the relay attack can be detected by adding an artificial ambiance channel between the smartphone and the transaction device using near-infrared light [65]. In addition, Ismaeel and Kamal showcased a system to control smart-home appliances using mobile near-infrared communications [77]. Despite the variety of their use cases, those techniques pertain to the necessity of highly specialized settings or equipment and are limited to designated scenarios.

6 DATA COLLECTION AND MODELING USING MOBILE NEAR-INFRARED METHODS

We then analyze the data collection and modeling methods using mobile NIR devices. Fundamentally, compared to stationary devices, mobile devices can be used for various contexts (*e.g.,* locations, ambient conditions, tasks). To this end, the data collected by mobile NIR devices can vary in accordance with the scenarios. In this section, we outline the datasets generated in recent studies using mobile NIR devices (Section 6.1). We further summarize the tasks, as the main motivations of modeling, that can be achieved using machine learning models, including regression tasks (Section 6.2) and classification tasks (Section 6.3).

6.1 Data collection

We first summarize the data collection outcomes in recent mobile NIR studies. We note that some studies (N=44) focus on proof-of-concept prototypes and thus do not include a thorough data

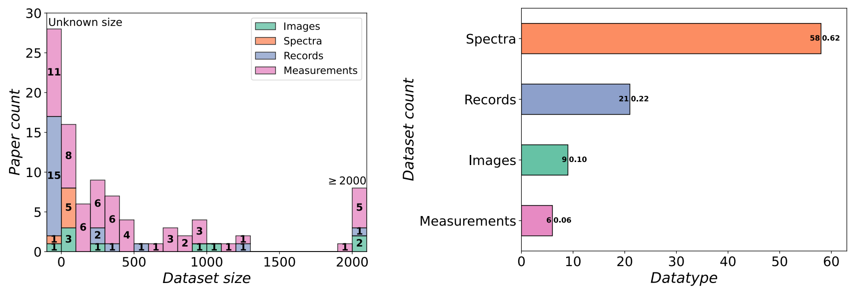

Fig. 5. Histogram of dataset sizes for mobile NIR studies.

collection process (*e.g.,* validating functionality with one user). Also, some studies (N=20) miss the necessary details for referring to the dataset size. Overall, we categorize the datasets as follows

- *NIRS spectra* – one dimensional spectral data by scanning objects using mobile NIRS devices. In total, 53203 NIRS spectra are reported by 47 studies (with 11 more studies missing details).
- *fNIRS records* – time series data outputted by monitoring the human brain's hemodynamic using mobile fNIRS devices. In total, 6609 records are reported by 6 studies (with 15 more studies missing details).
- *NIR images* – two-dimensional images outputted by mobile NIR imaging devices. In total, 44860 images are reported by 8 studies (with 1 study missing details).
- *Other NIR measurements* – data points in other formats outputted by other mobile NIR devices (*e.g.,* voltage values as sensor reading). In total, 157 measurements are reported by 5 studies (with 1 study missing details).

We further show the histogram of dataset sizes for recent studies using mobile NIR devices in Fig. 5. We can observe that most studies report datasets with less than 1000 samples, with several exceptional cases. In particular, Mayberry et al. collected ~40000 eye images in their study using their eye-tracking glass prototype [118]. The relatively large size of the dataset was due to the high sampling rate of up to $250 - 350Hz$. Another exceptional case was reported by Moon et al.. The authors collected 14714 NIRS spectra for salmon, tuna, and beef with different freshness conditions (fresh, likely spoiled, spoiled) [124]. The data collection was taken automatically every minute continuously for 30 hours, resulting in a relatively large dataset.

Based on the survey result, we include a comprehensive list of the datasets generated by recent mobile NIR studies in Appendix Table 5. As data collection can be correlated to the corresponding studies, it is recommended to refer to similar studies as the references for study design.

6.2 Regression tasks

We then provide a comprehensive analysis of regression tasks and modeling methods for mobile NIR studies, as summarized in Table 4, along with their advantages and disadvantages in mobile NIR sensing regression tasks. As a quick reference, we also provide a comprehensive list of the models that achieve the best performance for those regression tasks in Appendix Table 6.

Overall, regression tasks in mobile NIR typically involve predicting or estimating a target variable using spectral data as input. Common applications include estimating concentrations of specific substances, maturity level estimation [169], pupil position or size for eye-tracking [118], and sugarcane quality prediction [127]. Our survey shows that the partial least squares (PLS) regression model is the most frequently employed for mobile NIR sensing tasks. In particular, PLS is supreme in processing high-dimensional NIRS spectra, where each dimension represents a wavelength. This model is particularly effective due to its ability to handle collinearity among input variables, a common characteristic in NIRS data [22]. The PLS model projects both input and output variables

Table 4. Comparative analysis of regression models, ordered from general to specific use cases.

Model	Advantages	Disadvantages	Use cases	Ref.
PLS	Effective with correlated, multivariate NIR data	May oversimplify complex relationships	General NIR applications	[6, 7, 38, 46, 62, 119, 127, 139, 142, 153, 155, 169, 170, 175, 178]
SLR	Simple and effective for linear data	Not suitable for multivariate or non-linear data	Simple NIR datasets with linear correlations	[76, 80, 125, 171]
MLR	Suitable for multivariate linear data	Limited in handling non-linear relationships	Multivariate linear NIR analysis	[82]
RF	Robust, handles high dimensionality	Can be computationally intensive	Large, complex NIR datasets	[5, 75]
MLP	Highly flexible for non-linear relationships	Requires relatively large datasets; can easily overfit	Complex NIR patterns	[8, 56, 116, 118, 140]
RQGPR	Robust in handling noisy data	Computationally demanding	Noisy NIRS datasets	[67]
SVM	Accurate, effective for smaller datasets	Less effective for large datasets with noise	Small, specific NIR tasks	[191]
RoBoost-PLS	Robust in handling outliers	Requires careful tuning of parameters	Advanced NIR feature analysis	[36]
PLS-OPS	Improved prediction accuracy with enhanced variable selection	Requires complex selection process with expertise	High-dimensional, complex NIR data with expertise knowledge	[24]
Gradient-Boost	Effective in diverse and complex datasets	Prone to overfitting with small datasets	Diverse, large-scale NIRS data	[5]
ELM-TrAdaBoost	Adaptive boosting for complex data	Requires careful tuning of parameters	Challenging, non-standard NIR tasks	[185]
DT	Easy to interpret and understand	Prone to overfitting; less effective with complex data	Easily understandable NIR models	[79]

to a latent space, maximizing covariance between them. However, PLS models may oversimplify complex relationships in particular mobile NIR tasks (such as estimating concentrations of a complex or mixed content), rendering overfitting or performance drop. The single linear regression (SLR) model, compared to the PLS model, is rather simple. However, the SLR model is also widely used in mobile NIR regression tasks due to its intuition in interpretations and effectiveness in simple tasks, making it a viable choice for one-dimensional inputs, such as a specific wavelength effective for a particular task (*e.g.,* 940 nm for blood glucose measurement).

Beyond PLS and SLR, other regression models can be suitable for different use cases, as listed in Table 4. For example, multilayer perceptron (MLP) offers versatility in handling both linear and non-linear relationships, making it suitable for a range of mobile NIR applications [121]. Other models like multiple linear regression (MLR), rational quadratic gaussian process regression (RQGPR), support-vector machine (SVM), extreme learning machine with transfer adaboost (ELM-TrAdaBoost), and decision tree (DT) are also employed for specific tasks, each with its unique advantages and constraints, as elaborated in Appendix Table 6.

6.3 Classification tasks

In contrast to regression tasks, classification tasks in mobile NIR sensing are pivotal for identifying categories based on the sensing data. Typical applications include ingredient identification using NIR spectra (*e.g.,* identifying food powders [182–184], liquids [82, 98, 140], or pills [28, 93]), assessing fruit maturity level [1, 169], and biometric authentication using NIR imaging [135], as shown in Table 5. As a quick reference, we also provide a comprehensive list of models with best classification models for specific tasks in Appendix Table 7.

In our survey, we observe that SVM is prevalently used due to its effectiveness in high-dimensional spaces, as seen in various mobile NIR applications such as the aforementioned ingredient identification and biometric authentication [44, 135, 183, 184]. In particular, SVM is prevailing when data

Table 5. Comparative analysis of classification models, ordered from general to specific use cases.

Model	Advantages	Disadvantages	Use cases	Ref
SVM	Effective for high-dimensional data	Less effective for very large datasets	General NIR classification tasks	[28, 44, 66, 82, 83, 91, 98, 130, 153, 169, 183, 184]
RF	More interpretable, handles complex datasets	Can be less effective in high-dimensional data	Complex datasets requiring feature analysis	[82, 93, 115, 123, 162]
CNN	Excellent for image processing	Requires large datasets, high computational cost	NIR image classification	[72, 124, 182]
PLS	Effective for small datasets with collinear variables	May oversimplify relationships	Small datasets with collinear variables	[92, 98]
NB	Effective in probabilistic classification	Less accurate with imbalanced datasets	Probabilistic tasks with balanced data	[93, 148]
MLP	Handles non-linear data	Risk of overfitting, computationally demanding	Non-linear, diverse data tasks	[140, 157]
DT	Easy to interpret	Prone to overfitting, less effective with complex data	Simple, hierarchical decision-making tasks	[1, 135]
kNN	Helpful for feature distribution visualization	Less effective with noisy, large datasets	Small datasets with clear feature distinctions	[82]
LDA	Effective in dimensionality reduction	Less accurate with non-linear data	Discriminative analysis	[64]
HESCA	Improves accuracy through ensemble approach	Computationally expensive	Tasks requiring ensemble methods for accuracy	[98]
BNN	Energy-efficient	Lower accuracy compared to complex models	Energy-sensitive, simple tasks	[26]
J48	Simple to implement	Less accurate for complex datasets	Simple NIR classification tasks	[101]

points are fewer than dimensions, making it particularly suitable for mobile NIR tasks. However, SVM can be less effective for very large datasets with high dimensions due to its limitations in scalability and computation complexity in such cases [63]. Alternatively, the RF model is also widely used in mobile NIR classification tasks. Compared to SVM, RF can be less effective in high-dimensional spaces while providing greater interpretability. For example, as demonstrated in [82, 93], RF can be very useful in feature analysis. This is crucial for applications where understanding the relevance of specific features, such as wavelength importance in NIR spectra.

Other models like J48, CNN, NB, and MLP are selected for their specific strengths in different classification scenarios. For instance, J48's simplicity makes it ideal for straightforward classification tasks [101], whereas CNN excels in image-based classifications due to its superior processing capabilities [72, 124, 182]. We also recognize that some models may not deliver the highest performance but offer other benefits. For example, kNN, despite its limitations, is excellent for visualizing feature distributions [82]. The parallelization capability of RF enhances its applicability in handling large datasets efficiently [82, 93].

In summary, the choice of classification model in mobile NIR sensing should be guided not only by performance metrics but also by the specific characteristics of the dataset and the desired outcome of the analysis. Our comprehensive list of models and their use cases, as presented in Appendix Table 7, aims to aid researchers in selecting the most appropriate model for their specific mobile NIR sensing tasks.

7 AN OVERVIEW OF MOBILE NEAR-INFRARED SENSING STUDIES

Finally, in this section, we show an overview of mobile NIR methods. First, to show an overall picture of the hardware, we analyze the wavelength usage of mobile near-infrared studies (Section 7.2). Then, based on the survey results, we categorize the studies into particular application domains and analyze what application domains have focused on during the past decade (Section 7.1). Finally, to understand the overall study focus in mobile near-infrared sensing, we conduct a topic modeling to analyze the main research topics in this area. (Section 7.3).

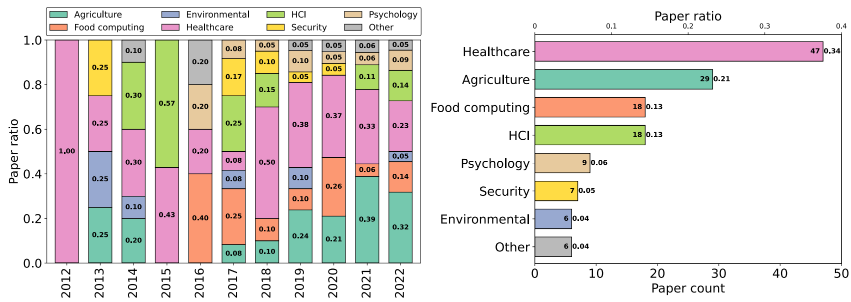

Fig. 6. Publication ratios by application areas, for each year (left), and cumulative (right).

7.1 Applications of Mobile Near-infrared Technologies

Furthermore, we analyze the applications for mobile NIR technologies. For each study, we first summarized its main use case concerning mobile NIR methods, then categorized the use cases to an application area. The application areas are

- *Agriculture* – including applications concerning crop plants and farming, such as leaf content analysis [164], soil content analysis [191], crop disease detection [148], and maturity level estimation [169].
- *Environmental* – including applications focusing on environmental sensing, such as water analysis [99], snow analysis [60], and studying wild animals [71] or wild plants [147].
- *Food computing* – including food sensing applications [120], such as food content analysis [83], drink content analysis [82], and food classification [140].
- *Human–computer interaction (HCI)* – including human-centered applications, such as gesture recognition [64], eye-tracking [118], and brain-machine interface (BMI) [130].
- *Healthcare* – including medical and health-related applications, such as monitoring glucose in blood [185], monitoring brain activity [2], disease diagnosis [4], assisting surgery [57], and pharmaceutical identification [93].
- *Psychology* – including studies related to mental attributes and conditions, such as measuring cognitive performance [133], drowsiness [66], fatigue [128], stress [108], and anxiety [117].
- *Security* – including computer security and surveillance-related applications, such as biometric authentication (*e.g.,* iris [72], hand vein [58]), attack detection [65], invisible labeling for privacy protection [103], and multi-band surveillance [69].
- *Other* – other mobile NIR applications that are not categorized due to their rarity, such as analyzing oil inhibitor content in electrical transformer [102], solid rocket propellant analysis [38], paint underdrawing identification [173] and monitoring vocal fold vibration [32].

We include a comprehensive application list in Appendix Table 8, as briefed in Fig. 6 for the application areas. We further categorize the application areas below

✔ **Mainstream** – *healthcare*. There are 47 (~34%) mobile NIR studies for *healthcare*. In the past decade, *healthcare* has been the most important application area and should maintain its significance in the near future. The main reason is that, as mentioned above, NIR light is 1) safe to the human body, 2) transmissive to human epithelial tissue (*e.g.,* skins), while 3) sensitive to some inner contents (*e.g.,* blood). Hence, NIR methods are ideal for non-invasive, rapid, and continuous physiological sensing. At the same time, mobile healthcare has become increasingly important (*e.g.,* home healthcare or remote healthcare) as the result of social issues such as population ageing [113]. As a result, *healthcare* remains the mainstream application for mobile NIR methods.

- **Emerging** – *agriculture* and *food computing*. There are 29 (~21%) and 18 (~13%) studies for *agriculture* and *food computing* respectively. Both areas received increased attention in recent years. It is worth noting that, albeit both areas concern food, *agriculture* focuses more on food production, while *food computing* focuses more on food consumption [120]. However, application scenarios for both areas pay attention to sensing methods that can be *in situ*, *i.e.,* mobile, rapid, without requiring carefully prepared samples – making mobile NIR methods suitable for both application areas. Furthermore, the underlying social issues such as shrinking farmlands and starvation also make both areas likely to remain important in the foreseeable future [104].
- **Incubating** – *HCI*, *psychology*, *security*, *environmental* and *other*. There are 18 (~13%), 9 (~6%), 7 (~5%), 6 (~4%), and 6 (~4%) studies for *HCI*, *psychology*, *security*, *environmental* and *other* application areas. We are yet to observe a clear trend for applying mobile NIR methods in these areas. The studies can be innovative but may lack a "killer application" (*i.e.,* a mobile NIR use case that is indispensable or superior to using alternative methods). For example, gesture recognition in HCI can be achieved by other wireless signals (*e.g.,* WiFi, RFID or radio-frequency identification, or acoustic) with better accuracy and usability [109], while cognitive analysis in psychology can be achieved by EEG with significantly lower cost but moderate performance [160]. However, we would like to highlight that, as mobile NIR technologies are still under active development (Section 5), there is great potential that "killer applications", likewise in *healthcare*, *agriculture* or *food computing*, can be "incubated" for these application areas.

7.2 Overview of Devices and Applications

We then show an overview of the connections between mobile near-infrared devices and applications. On one hand, the features of mobile near-infrared devices such as wavelengths, as detailed in Sections 4 and 5, directly influence their utility across different domains. On the other hand, the application trend itself also affects the development of mobile near-infrared devices, necessitating devices with specialized wavelength capabilities.

For example, in agriculture and food computing, the trend towards comprehensive quality assessment and non-invasive monitoring has led to the development of devices such as *AB Vista NIR4*, *TI NIRScan Nano* and *InnoSpectra NIR*, which offer broad wavelength ranges for detailed spectral analysis [13, 24, 62, 170, 176]. These devices can capture a wide array of information, making them versatile for various agricultural products and food ingredients.

In contrast, for the healthcare and psychology application domains, particularly in brain imaging and cognitive studies, the demands for precision, sensitivity, and mobility have driven the advancement of fNIRS systems such as the *'Brite' Artinis* series and prototypes for particular scenarios. These systems focus on specific wavelength ranges to accurately monitor hemodynamic activities, catering to the nuanced requirements of medical or psychological diagnostics and research [20, 44, 108, 115, 189].

Similarly, the emergence of more applications such as environmental monitoring, security, and other applications has motivated the development of mobile near-infrared sensing prototypes, such as particular device modalities for water monitoring [86, 99]. These prototypes are designed to meet specific environmental or industrial challenges, demonstrating how application demands can directly shape device innovation. As application trends continue to diversify, we can expect to see further advancements in near-infrared technology, with devices becoming either increasingly versatile or specialized to specific application domains in parallel.

In light of such trends, we note that there can be both challenges and opportunities for researchers and practitioners. In particular, the emergence of various applications such as agriculture, healthcare, and food computing necessitates a comprehensive understanding of near-infrared

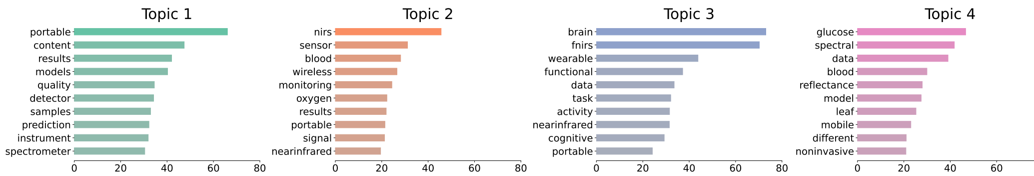

Fig. 7. Word distributions of topic modeling results based on Latent Dirichlet Allocation.

technology, especially in terms of wavelength selection and device capabilities. This trend also fosters interdisciplinary collaboration, as the effective use of near-infrared technology in diverse application domains often requires a blend of expertise from multiple fields.

7.3 Topic Modeling for Mobile Near-Infrared Sensing Studies

Finally, to understand the overall aspects of the mobile near-infrared sensing study area, we conduct a topic modeling based on the title and abstract of the included studies. In particular, we adopted the Latent Dirichlet Allocation model with 2 - 5 topics [18] (Fig. 7). Also, to find the most meaningful topics, we filtered the title and abstract with nouns (including common nouns and proper nouns) and adjectives using the NLTK tool [112]. The results were then reviewed separately. Finally, we identified the following 4-topic model to summarize the study topics in mobile NIR sensing.

Topic 1: Mobile NIR Sensing in Food Analysis – We observe this topic being predominantly associated with the application of mobile NIR sensing for food analysis. This topic correlates to the aforementioned agriculture and food computing application areas for food production and consumption respectively. In particular, the prominence of words such as “portable”, “content”, “quality”, “samples”, “spectrometer”, and “food” indicate an inclination towards the use of mobile NIR devices like NIRS for food content analysis. Further, we note the use of “models”, “prediction” and “detection” implying the adoption of machine learning models for predicting food quality or contents. Example studies include content analysis in liquid food [140] and juice [24], fruit maturity prediction [169], food allergen detection [83], and food freshness estimation [101].

Topic 2: Prototyping Mobile NIR Devices for Physiological Sensing – The second topic appears to revolve around the adoption of wireless and mobile NIR sensors in physiological sensing. In particular, words such as “nirs”, “blood” and “monitoring” indicate the usage of NIRS in blood and other physiological sensing. Furthermore, “wireless” and “portable” imply the mobility and usability of these devices. In addition, the mention of “design” and “devices” highlights the importance of the design process in developing efficient and effective mobile NIR sensing devices. This topic reflects the significance of studies for prototyping mobile NIR devices as we summarized in Section 5. Example studies include prototypes for blood oxygen monitoring [23], blood glucose estimation [80] and insulin detection [33].

Topic 3: Brain Activity Monitoring Using Wearable NIR Devices – We identify the third topic as the application of wearable NIR devices in human activity sensing. In particular, words like “brain”, “fnirs”, “wearable” and “task” denote the employment of fNIRS in monitoring human brain activity during various tasks. Similarly, “wireless”, “portable”, and “users” further denote the focus on making the device more accessible and user-friendly via prototyping. Example studies include stress analysis based on brain activity during sleeping [108], drowsiness monitoring using a miniaturized prototype [66], and 3D printed headband for flexible design [2].

Topic 4: Spectral Analysis for Noninvasive Mobile NIR Sensing – The fourth topic focuses on noninvasive sensing techniques. On one hand, NIRS can acquire spectral data without damaging the measuring objects, making it ideal for *in situ* analysis for various tasks. On the other hand, retrieving meaningful information for the spectral data can be challenging, as the spectrum includes

Table 6. Comparison of Mobile Near-Infrared Sensing with Alternative Methods

Modality	Advantages	Disadvantages	Key Applications	Challenges	Opportunities
NIR Sensing	Non-invasive, rapid, sensitive to chemical properties	Limited penetration depth, sensitive to environmental changes	Agriculture, food computing, medical diagnostics	Material variability, environmental noise	Algorithm and hardware improvements, multimodal sensing
Computer Vision (RGB)	Rich visual details, wide availability	Limited to surface analysis, affected by lighting conditions	Object recognition, surveillance	Lighting variations, complex context, occlusions	AI-based image processing, enhanced sensors
X-Ray	High penetration ability, detailed internal imaging	Exposure to radiation, limited to internal structure analysis	Medical diagnostics, security scanning	Radiation exposure, image interpretation	Radiation shielding, digital imaging enhancements
Ultrasound	Penetrates soft tissues, real-time imaging	Limited penetration depth, requires contact	Medical imaging, industrial testing	Operator skill, image quality	3D imaging techniques, automated analysis
IMU	Accurate motion tracking, low-cost, small size	Affected by drift, limited to motion detection	Wearable devices, activity monitoring	Signal drift, data interpretation	Sensor fusion, calibration techniques
Laser	High precision, long-range, robust to light changes	Expensive, eye safety concerns	LiDAR, distance measurement, industrial automation	Cost, safety regulations	Eye-safe lasers, cost reduction
WiFi CSI	Ubiquitous, non-intrusive, works through walls	Lower resolution, affected by environmental factors	Indoor localization, activity recognition	Multipath interference, multi-user scenarios	Signal processing advancements, deep-learning methods
mm-Wave Radar	High resolution, not affected by lighting	Expensive, limited signal range	Automotive radar, high-precision positioning and tracking	Deployment in complex environment, hardware cost	Antenna array design, control and processing algorithms

mixed information about the measurement target. Hence, spectral analysis is an important topic for mobile NIRS. A common way is to adopt machine learning models as we summarized in Section 6. Furthermore, Words like "glucose" and "leaf" imply the use of NIRS in healthcare, environmental, and agriculture areas. Example studies include blood glucose monitoring [161], dairy farm forage quality analysis [13], and water monitoring [3].

Notes on Mobile NIR Study Topics – Overall, we can observe several highlights on all four topics. For instance, all topics underscore the significance of making mobile NIR sensing applications more accessible and convenient. Also, they all imply the correlation between the sensing methods and scenarios. That is, from the perspective of data collection and modeling, it is important to choose the right sensing techniques and algorithms for particular scenarios. There is yet a universal solution for most use cases. Moreover, as a reflection of the applications (Section 7.1), there is a clear highlight on non-invasive, wireless, and wearable technologies across healthcare and food-related topics. Compared with alternative methods, the usability and non-invasive features make mobile NIR sensing preferred in those application areas. For that, the importance of "design" implies the ongoing innovation and evolution in mobile NIR devices.

8 CHALLENGES AND FUTURE DIRECTIONS

Finally, we discuss the main challenges for mobile NIR studies and corresponding future directions, concerning multimodal and alternative sensing methods (Section 8.1), modeling (Section 8.2), applications (Section 8.3), and data and security (Section 8.4).

8.1 Comparison and Multimodal Sensing with Alternative Methods

The main advantage of near-infrared sensing is to provide detailed information regarding the object's chemical compound in a non-invasive and rapid way [22, 85]. This makes mobile near-infrared sensing prevalent in material sensing compared with alternative methods, especially in mobile contexts that requires *in situ* analysis as shown in our survey. However, it also faces inherent challenges with limited effectiveness. For a comprehensive comparison, we summarize the key advantages and disadvantages of mobile near-infrared sensing and alternative methods in Table 6, and then discuss future directions of multimodal sensing to address the challenges in mobile near-infrared sensing.

Key challenges of mobile near-infrared sensing – Our survey highlights multiple challenges when using near-infrared sensing in a mobile context. A main disadvantage is that near-infrared cannot penetrate many opaque materials in-depth. In particular, while near-infrared has been widely used in healthcare for sensing blood such as glucose and hemoglobin that is under the skin (Section 7.1), it cannot provide more information on deeper tissues such as organs and bones. Alternatively, X-ray and ultrasound are alternatives for such applications, with different disadvantages such as safety concerns (X-ray) and operator skill requirements (ultrasound) [73, 85].

Another main disadvantage of mobile near-infrared sensing is its susceptibility to environmental changes, especially motions in the mobile sensing context. Such changes can interfere with the signals significantly and cause a performance drop. For example, a study by Siddiquee et al. focused on removing signal distortions caused by human movement when measuring brain activities using fNIRS [152]. Similarly, multiple studies developed different modalities to alleviate such issues in mobile NIRS sensing tasks, as we summarized in Section 5.

Multi-modal sensing in future work – A promising way to address these challenges is to adopt multimodal sensing by fusing other sensing methods. For example, the aforementioned study by Siddiquee et al. utilized IMU sensors to estimate human movements for removing interference in mobile fNIRS [152]. Nevertheless, the method can only work with wearables where the sensors must be attached to the body. Alternatively, Computer Vision (CV) and WiFi CSI-based sensing methods are effective in monitoring human activities that are more versatile and can be used in broader scenarios [114].

Similarly, combining mobile near-infrared sensing with CV can further enhance applications in agriculture such as crop monitoring. On one hand, existing CV studies utilizing RGB cameras for smart agriculture focus on texture-based analysis [137], while near-infrared sensing such NIRS and NIR imaging can provide chemical properties of crops. This fusion enables comprehensive crop health assessment, overcoming the limitations of either method alone. Such method can also be used in remote sensing, medical diagnosis, HCI, and security, as demonstrated by several studies in particular scenarios (*e.g.,* fruit quality monitoring [154], embedding information in 3D printing [84], biometric identification [135]).

Other mobile sensing methods, such as laser-based ranging and Millimeter Wave (mm-Wave), can also compensate for NIR sensing methods in a mobile context. For example, laser and mm-Wave can provide rich context information such as objects' positions or distances in outdoor scenarios. Combined with NIR sensing, this information can be useful in applications like environmental monitoring and hazard detection. In such scenarios, NIR sensing can identify chemical characteristics or changes in vegetation, while laser and mm-Wave sensing offer critical data on topography and physical obstructions. This allows for a comprehensive analysis of environmental conditions, aiding in the early detection of potential hazards. Additionally, in agricultural applications, the fusion of these technologies facilitates precise mapping of crop fields, enabling targeted treatments based on spatial distribution and derived crop health insights based on NIR sensing [67]. The integration of near-infrared with laser and mm-Wave sensing enhances decision-making processes, leading to more effective and efficient outcomes in various mobile sensing applications.

In summary, the integration of NIR sensing with other mobile sensing methods represents a significant research opportunity. The multimodal approaches can effectively leverage the strengths of diverse sensing technologies. This can help address the inherent limitations of mobile NIR sensing and enable more sophisticated applications.

8.2 Machine learning methods for mobile NIR sensing

With the availability of datasets, researchers can then focus on improving algorithms for mobile NIR sensing methods, particularly with machine learning methods. The main challenge for modeling a mobile NIR sensing task is the tradeoff between scalability and computational cost.

Scalability consideration – First of all, most existing studies only adopt conventional machine learning methods (Section 6.2 and 6.3). Certainly, conventional machine learning methods can achieve acceptable performances with low computational costs. However, those models can only be used for a specific task and may not be transferred to other tasks. In practice, users have to change or train a new model once the scenario is changed, with a strong assumption that the users already know what the task is. For example, Jiang et al. used the same NIRS hardware but trained different machine learning models for different liquid contents [82], while users have to know the content categories beforehand (*e.g.,* sugar, alcohol or milk). Conventional machine learning methods, nevertheless, have limited learning capacity and scalability and can yield significant performance loss for more complex tasks (*e.g.,* classifying liquid contents using NIRS without prior knowledge, with hundreds of possible categories and a large dataset) [190].

In addition, certain mobile NIR sensing tasks also require more sophisticated machine learning models to achieve better results. For example, recent studies in artificial intelligence (AI) show that deep learning models can achieve significantly better performances on image processing [132] and time-series data processing tasks [78]. In particular, with higher NIR imaging resolutions and more fNIRS channels, conventional machine learning methods will be further disadvantaged.

Computational consideration – While deep learning methods have demonstrated superior performance, they have not been widely adopted in mobile NIR sensing tasks. In addition to the aforementioned dataset limitations, deep learning algorithms are predominantly computationally intensive, posing a considerable challenge when applied to mobile devices that are constrained in their computational capacity and energy resources [29].

To address this issue, a possible solution could be transferring raw data to a remote or edge server that runs the deep learning model and returning the inference results to mobile devices (*e.g.,* the study in [3] used a remote server for data analysis). However, this method requires significant networking resources such as transmission. It also raises additional concerns including latency and privacy [40], in particular for the mobile sensing tasks that involve human subjects such as fNIRS.

Alternatively, the prospect of integrating a deep-learning-enabled chip within mobile devices is being explored (*e.g.,* many mobile System-on-Chip (SoC) solutions support deep learning difference [168]). This method integrates deep learning capabilities directly into mobile devices in a more energy-efficient way, and bypasses the need for data transmission (*e.g.,* the study in [43] used on-device near-infrared imaging processing algorithm in a smartphone). However, this can complex the hardware architecture, making mobile near-infrared devices a less feasible solution compared to alternative techniques (*e.g.,* NIRS is cheaper than high-accurate laboratory test, while fNIRS is much cheaper than the high-resolution fMRI).

Furthermore, we recognize that different NIR sensing tasks have varied computational requirements. The analysis of high-dimensional spectral data derived from the NIRS method, or multichannel time-series signals from the fNIRS method, may require disparate computational strategies (*e.g.,* fNIRS may require real-time processing). Therefore, algorithmic optimization for these tasks must be considered for these distinctive computational needs.

The tradeoff and opportunities – There are several ways to achieve a tradeoff between scalability and computational cost. One promising way is to design a compact model for mobile devices [179]. However, such a method is still limited by the computational and energy resources for mobile devices, in particular for relatively complex tasks. An alternative solution can be only partially processing data in the local devices, with an optimization target to achieve relatively low energy consumption and delay, while maintaining data privacy and high performances [187]. The inclusion of edge computing techniques [187], federated learning [110], and on-device AI [48] also offer promising avenues to help alleviate some of these computational constraints and open up new opportunities for mobile NIR sensing tasks.

The research gap, however, is that current studies predominantly focus on deep learning tasks using datasets collected in particular scenarios (such as image classification and object detection) and may not be directly applicable to mobile NIR sensing tasks. Many mobile NIR sensing tasks require *in situ* analysis such as detecting food allergen in food computing [83], or "in the wild" data collection such as environmental sensing [3], or both. The requirements of these tasks can significantly differ from those in different scenarios. Moreover, NIR data are unique in their nature. For instance, NIRS results in high-dimensional spectral data, whereas fNIRS generates multi-channel time-series signals. With spectral NIR imaging, the data can be more intricate than typical images, with more channels at different wavelengths than the basic red-green-blue (RGB) channels. To the best of our knowledge, and according to our survey results, there are not many studies focusing on optimizing mobile NIR sensing tasks, leaving a research gap for future studies.

8.3 Human factors in mobile NIR applications

Next, besides the advancement of mobile NIR sensing methods, it is also crucial to expand the application areas in practice. As we observed in Section 7.1, beyond the mainstream *healthcare* studies, there are great potentials for mobile NIR sensing to be further adopted in more areas such as *agriculture*, *food computing* and *HCI*.

However, many existing studies for mobile NIR sensing focus on the technical aspects while underestimating *human factors*. In fact, compared with stationary setups, mobile devices are highly correlated with user behaviors [42]. For instance, a typical *food computing* application involves a user acquiring some data for the food as the input (*e.g.*, a NIRS spectrum or a photo), while the output (*e.g.*, food category or composition) can be impacted by how the data are acquired (*e.g.*, different angles or distances) [94, 120]. This leaves a significant research gap for bringing a mobile NIR sensing technology into real-life [95, 120].

To this end, for incubating more practical applications, future work for mobile NIR sensing applications should also consider human factors in both design and evaluations. For example, Siddiquee et al. presented a method to remove motion artifacts from mobile fNIRS signals, making it more practical for real-life applications such brain-machine interface [152]. Also, for the same technology, different interface designs may even impact users' trust towards the technology, which can eventually affect the growth of the application area, as shown by Jiang et al. in a gluten detection task using mobile NIRS [83].

In summary, we believe an important direction for mobile NIR sensing is to incorporate more *human factors* in future studies. As a result, in practice, mobile NIR sensing methods can be better adopted, accepted, and used by more users.

8.4 Data availability and security in mobile NIR sensing

Data availability – Beyond algorithms, a fundamental issue that hinders mobile NIR research is dataset availability. Many researchers have to generate their own datasets for further studies. This not only limits mobile NIR studies to those who can access or build the devices, but also prevents researchers from cross-validates their findings by referring to datasets generated by others, resulting in less connection among the mobile NIR sensing studies. To date, there are limited open-sourced NIR datasets available that are either for particular scenarios or with relatively small sizes. Existing NIR datasets include the CASIA NIR-VIS Face Database (725 subjects, 17580 images) [105] for

NIR imaging, unilateral finger- and foot-tapping dataset (30 participants) [9] and openFNIRS[4] (12 datasets with 5-43 participants) for fNIRS, and global soil VIS-NIRS database [11].

Nevertheless, as we shown in Section 6.1 and Appendix Table 5, there are ~100 mobile NIR datasets generated in the past decade, while few of them are open-sourced (*e.g.,* hand vein images in [39] and [58]). In addition, datasets in Appendix Table 5 are collected using mobile devices that can be more practical in real-life settings. Hence, it would be highly beneficial for researchers and developers to have access to those datasets.

A potential solution is by adopting the Open Science framework [53, 163]. In recent years, there has been an increased demand for making research projects, study designs, datasets, source codes, and tools publicly or partially available to others [163]. The main concern, however, is privacy issues. For example, many fNIRS data include participants' brain activities that can be highly sensitive. A promising way to address this issue is to cede the ownership of the data to the participants [41]. Datasets with privacy concerns can only be published with the consent of the who generated them instead of the researchers. Other datasets without such issues can be then published by researchers using the Open Science framework [53].

Data security – In addition to the data availability issue, there are missing data security-related studies in mobile near-infrared sensing. Our survey identifies several security-related applications using mobile near-infrared techniques, such as biometric recognition-based authentication methods using vein patterns [58] or iris patterns [72]. However, few studies focused on data security. Mobile NIR sensing, like any other data-intensive technology, can be susceptible to various forms of security threats, such as unauthorized access, data leakage, and manipulation of the data.

At the current stage, mobile near-infrared devices are mostly used by researchers and developers who are responsible for data security. And thus the data are mostly managed in a laboratory standard. Nevertheless, in the future, we envision that mobile near-infrared devices can be adopted in broader scenarios For example, our survey identifies several studies that show fNIRS can be used as a human-computer interface [91, 157, 165]). Also, mobile NIRS can be widely adopted in food computing such as food freshness prediction [124]. allergen detection [83], and Calorie estimation [75]. Hence, the significance of security concerns escalates in mobile scenarios in the future. First, the devices will be mostly managed by end-users who are not necessarily trained for data protection, making them more exposed to security threats. Second, mobile devices are often personal, containing rich sensitive information about individuals, thereby intensifying the need for robust security methods. For instance, NIRS data used in healthcare applications can include highly sensitive personal health information. Without appropriate data security protection, there are risks of exposure that can lead to privacy invasion, identity theft, or insurance fraud.

Furthermore, we highlight that data security in mobile near-infrared sensing involves two primary dimensions - the security of the data in collection, communication, and storage. Firstly, as near-infrared sensing utilizes light transmission and reflection, there can be light leakage that can be detected by eavesdropping. Previous studies also indicate the device can be identified based on the sensing data, leading to device usage data or even user data leakage [19]. Second, many mobile NIR devices provide wireless connections to transmit data to an edge device for processing or storage (*e.g.,* miniaturized NIRS using Bluetooth to transmit data to mobile phones [51, 142]) without encryption. The transmission can be easily captured by other wireless devices, resulting in data leakage. Third, the collected data by mobile NIR mobile devices are mostly stored in plain format without encryption, leaving a risk of unauthorized access. Hence, security features should be designed to protect data. For instance, leakage-prevention mechanisms should be designed to prevent eavesdropping during data collection. Also, encryption techniques and rigorous access

[4]https://openfnirs.org/

control and authentication mechanisms should be employed to protect the data in transmission and storage, preventing unauthorized access to the data.

In summary, while much work has been done to secure mobile data in general, studies on the specific challenges related to data security on mobile near-infrared sensing methods are still missing. Future studies should address this gap by developing innovative security methods tailored to the unique characteristics and requirements of mobile near-infrared sensing (*e.g.,* eavesdropping during data collection). With the growth of mobile near-infrared sensing devices, the data security challenge becomes increasingly critical.

9 CONCLUSION

In this survey, we systematically reviewed recent studies in mobile NIR sensing methods including devices, data collection, modeling, and applications. In particular, we observe that studies concerning mobile computing are popular. We also note that there are many challenges and opportunities for this study area including the lack of datasets, modeling, applications and data security that should be addressed in future studies.

We also note several limitations to our survey. First, as we only considered studies that explicitly involve mobile NIR methods, there may be studies that are not included in this survey but utilize mobile NIR as their underlying technology. Also, we only included studies from the past decade (2012 - 2022). However, as mobile NIR devices are emerging recently, earlier studies can be limited by hardware that may be obsolete. Finally, as our survey aims to give an overview of the study area, we do not provide a more in-depth analysis of the technology itself. Further surveys can focus on one aspect with more detailed reviews (*e.g.,* device, data collection, modeling, or application).

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Appendix

Appendix A MOBILE NEAR-INFRARED PROTOTYPES

We provide a comprehensive list of prototypes from recent studies using mobile near-infrared (NIR) sensing methods. For analysis, please refer to Section 5.

Appendix Table 1. Prototypes using NIRS method developed in recent studies.

Ref.	Use cases	Wavelengths (nm)	Computing	Connectivity				UI & apps		
[186]	Analyzing corn leaf	450, 600, 880	Raspberry Pi	✓						
[51]	Analyzing dairy farm forage quality	900 - 1700[1]	LOLIN D32		✓	✓			✓	✓
[142]	Analyzing dairy farm forage quality	900 - 1700[1]	TI TM4C129		✓	✓			✓	
[82]	Analyzing everyday drinks	900 - 1700[1]	Raspberry Pi	✓	✓			✓		
[75]	Analyzing food nutrients	940, 1050, 1200, 1300, 1450, 1550, 1650	Arduino		✓	✓	✓		✓	
[3]	Analyzing glyphosate residues in waters	410 - 940[2]	ESP32		✓	✓	✓		✓	✓
[76]	Analyzing liquid contents	510, 880	smartphone		✓				✓	
[102]	Analyzing transformer oil inhibitor content	1388 - 1412	Raspberry Pi	✓	✓			✓		
[12]	Assessing sleep apnea	700 - 1000	BGM121 SiP			✓				
[92]	Classifying mango maturity index	1350 - 2500[3]	Raspberry Pi	✓	✓		✓	✓		
[47]	Detecting extravasation during injection	760, 850	TI CC3200		✓		✓	✓		
[1]	Detecting fruit quality	520, 670, 920, 970, 1050, 1320	Arduino	✓				✓		
[169]	Detecting fruit quality and maturity level	900 - 1700[1]	ESP8266Ex				✓		✓	
[83]	Detecting gluten in bread	900 - 1700[1]	TI TM4C129		✓	✓	✓		✓	
[33]	Detecting insulin and glucose in blood	850, 890, 935, 950	Atmega32				✓	✓		
[125]	Detecting milk adulterations	970, 1450, 1200	NXP HCS08	✓	✓			✓		
[178]	Detecting milk composition	650 - 1100[2]	Raspberry Pi	✓	✓		✓	✓		

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Appendix Table 1 – *continued from previous page*

Ref.	**Use cases / motivation**	**Wavelengths (nm)**	**Computing**	**Connectivity**				**UI & apps**		
[46]	Detecting soil nitrogen	1300 - 2400	Raspberry Pi			✓			✓	
[191]	Detecting soil nitrogen and moisture	1260, 1330, 1360, 1430, 1530, 1580, 1660, 1450	NXP JN5139	✓				✓	✓	
[50]	Diagnosing breast cancer	740, 810, 850	ATmega328			✓			✓	
[79]	Estimating glucose in blood	800 - 1000	Arduino, Raspberry Pi	✓						
[67]	Estimating leaf nitrogen and water	450, 500, 550, 570, 600, 610, 680, 730, 760, 810, 860	Raspberry Pi	✓	✓			✓		
[6]	Estimating sugar content in breakfast cereals	1350 - 2560[3]	unspecified		✓	✓			✓	
[10]	Estimating watermelon ripeness	unspecified	Raspberry Pi	✓				✓		
[93]	Identifying pharmaceuticals	900 - 1700[1]	TI TM4C129		✓	✓			✓	
[28]	Identifying pharmaceuticals	900 - 1700[1]	TI TM4C129		✓	✓			✓	
[37]	Monitoring blood oxygen and heart rate	660, 910	CC2540			✓			✓	
[23]	Monitoring blood oxygen and heart rate	660, 940	CC3200				✓		✓	
[80]	Monitoring glucose and bilirubin in blood	470, 940, 1550, 1650	ATMega32			✓		✓	✓	
[54]	Monitoring glucose in blood	850, 880, 940	ATmega328			✓			✓	
[185]	Monitoring glucose in blood	900 - 1700[1]	TI TM4C129		✓	✓			✓	
[161]	Monitoring glucose in blood	630, 940	Arduino			✓			✓	
[59]	N/A (a design for mobile NIRS prototype)	900 - 1700[1]	TI TM4C129	✓	✓	✓			✓	✓
[139]	Predicting moisture content in C. oleifera seeds	900 - 1700[1]	TI TM4C129			✓			✓	
[7]	Screening soybean quality	1350 - 2560[3]	unspecified		✓	✓			✓	

[1] Based on NIRScan Nano.
[2] Based on STS-NIR.
[3] Based on Si-Ware NeoSpectra-Micro.

Appendix Table 2. Prototypes using fNIRS method developed in recent studies

Ref.	Motivation	Wavelengths (nm)	#Ch	Computing	Connectivity				UI & apps		
[145]	Improving usability, configurable remotely	770, 850	10	Raspberry Pi				✓			✓
[66]	Improving usability, multimodal sensing	670, 850	2[1]	Custom SoC			✓			✓	
[17]	Monitoring water concentration in blood	735, 780, 810	12	Microchip DSPIC				✓			
[180]	Monitoring muscle activity	730, 805, 850	6	TI MSP430			✓				✓
[188]	Improving usability, low-cost	760, 850	1	nRF SoC			✓				
[146]	Improving usability and SNR	770, 850	2	Raspberry Pi				✓			✓
[64]	Multimodal muscle activity monitoring	730, 805, 850	4[2]	TI MSP430			✓				✓
[130]	fNIRS-BMI feasibility study	780, 805, 830	8	unspecified				✓			✓
[181]	Improving usability and spatial resolution	735, 850	128	mbed LPC1768		✓		✓			✓
[100]	Improving usability and SNR	730, 850	8	STM32			✓				
[2]	Improving usability, low-cost	770, 830	10	ATmega32U4			✓			✓	
[172]	Improving usability, released as a product	735, 810, 850	2	unspecified			✓			✓	✓
[91]	Developing fNIRS-BMI system	735, 810, 850	2	unspecified			✓			✓	✓
[165]	Developing mutimodal BMI system	750, 850	6[3]	Cortex M4			✓				
[152]	Improving SNR during motion	850	2[4]	TI CC3200				✓			
[151]	Improving usability	760, 840	2	TI CC2540			✓			✓	
[26]	Increasing energy efficiency	735, 850	18	FPGA		✓		✓			✓

[1] 1 fNIRS + 1 EEG, [2] fNIRS + sEMG hybrid, [3] 2 fNIRS + 4 EEG, [4] with + without motion.

Appendix Table 3. Prototypes using NIR imaging method developed in recent studies

Ref.	Use cases / Motivations	Wavelengths (nm)	Computing	Connectivity				UI & apps		
[158]	Analyzing conservation and restoration of paper-based artifacts	248 - 1050	unspecified	✓				✓		
[30]	Detecting breast tumor	600 - 1000	XC3S1000 FT256 FPGA			✓		✓		
[4]	Detecting colorectal cancer cell	673, 702	Arduino	✓				✓		
[167]	Detecting pupil and glint	850	unspecified	✓				✓		
[49]	Dorsal hand vein imaging	850	unspecified				✓		✓	
[43]	Embedding interactive tags into 3D prints	800 - 850	Raspberry Pi NoIR	✓				✓	✓	
[106]	Eye-tracking	940	TI MSP432	✓						
[118]	Eye-tracking	Unspecified	STM32		✓					
[174]	Gesture recognition	Unspecified	Atmel SAMA5D31		✓	✓				
[57]	Image guided surgery	820	XEM3050 FPGA		✓					
[71]	Localization of bats	Unspecified	Rapberry Pi, Zynq-7000 FPGA SoC	✓	✓		✓	✓		
[36]	Predicting biochemical variables of grape berries	400 - 1000	unspecified	✓				✓		
[58]	Recognizing vein biometric	960	smartphone	✓					✓	
[69]	Security and surveillance	750 - 1100	unspecified	✓						
[131]	Surgery assistant	760, 830	Jetson TX-2	✓				✓		
[39]	Vascular pattern of hand-veins imaging	940	smartphone		✓				✓	
[34]	Vein imaging	850 - 890	unspecified	✓			✓	✓		

Appendix Table 4. Prototypes using other NIR sensing methods developed in recent studies.

Ref.	Use cases	Wavelengths (nm)	Computing	Connectivity				UI & apps		
[60]	Analyzing snow optically equivalent diameter (OED)	950	TI MSP430	✓				✓		
[122]	Detecting bladder filling to capacity	950	TI MSP430	✓						✓
[171]	Detecting tea polyphenol detection for quality control	765	STM32	✓	✓			✓		
[111]	Estimating blood pressure	525, 630, 850, 940[1]	TI MSP432			✓				
[123]	Measuring interaction proxemics	950	nrf51822 SoC	✓	✓					
[55]	Monitoring blood oxygen and heart rate	660, 940[1]	TI MSP430				✓			
[116]	Monitoring glucose and bilirubin in blood	940[1]	unspecified			✓		✓	✓	
[97]	Monitoring glucose in blood	940	unspecified		✓	✓				
[21]	Monitoring glucose in blood	1550	Arduino	✓				✓		
[81]	Monitoring glucose in blood	unspecified	Raspberry Pi	✓	✓			✓		
[32]	Vocal fold vibration monitoring	850[2]	N/A							

[1] Using photoplethysmography (PPG).
[2] Using photoglottography (PGG).

Appendix B MOBILE NEAR-INFRARED DATA COLLECTION

We provide a comprehensive list of datasets generated from recent studies using mobile near-infrared (NIR) sensing methods. For analysis, please refer to Section 6.1.

Appendix Table 5. NIR-related dataset generated in recent studies.

Ref.	Dataset	Description
[118]	~40000 eye images	~2500 eye images each participant, 16 participants
[124]	14714 food spectra	1031, 1042, 1129 for salmon (Atlantic), 1055, 1095, 1457 for salmon (Pacific), 840, 978, 1045 for Tuna, 1545, 1803, 1694 for Beef, for 3 conditions of fresh, likely spoiled, spoiled, respectively. 15, 15, 17, 16 samples each food, 1 min per scan
[75]	12500 spectra	500 scanes per sample, 1 sample per food, 25 foods
[117]	4000 fNIRS records	58 participants, all with 180 sec of resting condition, 19 "younger" participants with 60 sec of mental arithmetic task
[82]	3654 liquid spectra	Modeling: 450 spectra (225/225 spectra for train/test, 18 spectra per sample, 25 sucrose solutions with 0 - 20 g/100ml concentrations) Testing: 2916 spectra (18 spectra per sample, 18 everyday drink samples, 9 ambient conditions) Testing: 243 spectra (3 spectra per sample, 9 sugar samples containing glucose, fructose, and their mixture with 5, 10, 15 g/100ml concentrations, 9 ambient conditions) Testing: 45 spectra (3 spectra per sample, 15 samples containing diluted liquor, milk, perfume with 0%, 25%, 50%, 75%, 100% of water volume)
[58]	2500 wrist images	50 participants with 100 wrists, 25 images per wrist), database open source
[31]	2228 forage spectra	over 600 haylage, corn silage and total mixed ration samples were collected
[98]	2000+ alcohol spectra	3 spectra per sample, 3 samples per solution for 40%, 35%, 38% alcohols, 40% alcohol + 1%, 2%, 5% methanol, in 44 bottles
[8]	1980 spectra	3 scans per position, 10 positions per sample, 66 samples from 6 groups with 11 adulteration levels each
[130]	1200 fNIRS records	3 participants, 40 trials per session, 30 sessions in total, including 4 daily-living actions
[183]	1200 food powder spectra	1000/200 spectra for train/test, 150 spectra each sample, 8 food powder samples
[83]	1134 tortilla wrap spectra	Modeling: 486 spectra (3 scans per location, 3 locations per sample, 3 samples per product with different package conditions, 18 tortilla wrap products with 9 gluten-free) Testing: 648 spectra (18 spectra each participant, 36 participants)
[72]	1008 iris images	28 participants, with 56 irises
[184]	960 food powder spectra	800/160 spectra for train/test, 8 food powders of salt, sugar, cream, flour, bean, corn, rice, potato

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Appendix Table 5 – *continued from previous page*

Ref.	Dataset	Description
[155]	930 turmeric powder spectra	30 spectra per sample, 31 powdered turmeric samples from commercial, farms and traders
[39]	920 hand vein images	31 participants, open-sourced
[142]	900 alfalfa spectra	1 spectrum each sample position, 10 positions per sample, 90 alfalfa samples
[56]	864 berry tissue spectra	2 spectra per sample, 216 berry samples per cultivar, 2 cultivars, 648/216 spectra for train/test
[182]	800 food powder spectra	640/160 spectra for train/test, 100 spectra each sample, 8 food powder samples
[169]	720 berry spectra	3 spectra each samples, 240 sweet cherries samples from 4 cherry tree
[170]	720 tea leaf spectra	10 spectra each sample, 72 leaf samples from 2 varieties of tea plants
[92]	700 spectra	4 locations per sample, 175 samples
[153]	600 spectra	150 spectra per group, 4 groups
[64]	520 fNIRS records	1 participant, 10 trials each gesture, 13 gestures, repeated 4 times in 4 different days
[62]	~480 tobacco spectra	360/120 spectra for train/test, 2 spectra each sample, 240 tobacco samples, total sugar, reducing sugar, nicotine, total nitrogen
[93]	480 pill spectra	Modeling: 400 spectra (1 spectrum each sample, 20 samples per category, 20 categories of pills) User study: 80 spectra (8 participants from care workers, 10 scans each participant)
[38]	472 propellant spectra	8 spectra removed from total 480 spectra, 20 mix iterations of CL-01 propellant
[28]	450 pill spectra	1 spectrum each sample, 20/5 samples per category for train/test, 18 categories of pills
[149]	396 fNIRS records	18 data points per participant, 22 participants
[7]	366 soybean spectra	3 spectra per sample, 107 soybean samples, 15 soybean product samples
[164]	350 winter wheat leaf spectra	Feekes growth stage 5, 6, and 9 for winter wheat, 64 experimental plots
[147]	349 macrophyte spectra	16 macrophyte species, 7 locations, scanned in different time
[178]	320 milk spectra	1 spectrum each sample, with 120/40 raw milk samples, 120/40 homogenized milk samples for train/test

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Appendix Table 5 – *continued from previous page*

Ref.	Dataset	Description
[67]	307 leaf spectra	Nitrogen experiment: 121 spectra (1 spectrum each sample, 121 leaf samples, N fertilization at 0, 6, 12, 20 $g \cdot L$, 3 times per week, in 64 plants, 4 species – canola, corn, soybeans, wheat) Water experiment: 186 spectra (1 spectrum each sample, 186 leaf samples, water applications at 50, 100, 150, 200 mL, 3 times per week, in 64 plants, 4 species – canola, corn, soybeans, wheat)
[148]	300 leaf spectra	25 spectra per plant sample, 12 plant samples with 2 genotypes in control and infested groups
[36]	274 images	126, 63, 85 images for Syrah, Fer-Servadou, Mauzac grape barries, respectively
[115]	273 records	13 records per participant, 21 participants
[136]	269 leaf spectra	Modeling: 207 spectra (104 spectra from diseased plants, 103 from healthy plants) Testing: 62 spectra (30 spectra from diseased plants, 32 from healthy plants)
[26]	240 spectra	12 participants, 20 data points per participant, 30 seconds per data point
[176]	230 spectra	1 scan per sample, 10 samples per batch, 23 batches from 8 medicines
[162]	220 records	10 participants, 22 data points per participant for 4 tasks
[46]	210 soil spectra	Modeling: 200 spectra (120/76 spectra for train/test, 4 spectra invalid, 5 spectra per sample at different locations, 40 soil samples) Testing: 10 spectra (10 soil samples)
[119]	204 spectra	3 scans per sample, 68 samples
[79]	200 glucose solution spectra	140/60 spectra for train/test, over 200 glucose solutions with 0.5 - 3 mg/dL concentrations
[139]	184 spectra	1 scan per sample, 184 samples
[191]	160 soil spectra	80 soil total nitrogen and 80 soil moisture
[52]	150 cotton canopy spectra	30 spectra each class, 5 classes of non-thermal-treated, N75-T25, N50-T50, N25-T75, thermal-treated
[126]	140 bread spread spectra	20 spectra per sample, spreads blended with saturated fatty acid at 0, 0.01, 0.02, 0.05, 0.10, 0.20, 0.50 g/g
[1]	140 apple spectra	140 apple samples with 70 ripe and 70 unripe
[127]	134 sugarcane spectra	1 spectrum each sample, 24 FS samples, 24 CJ samples, 24 RJ samples, 31 SCS samples, 31 SS samples
[135]	92 left hand images	10 participants, 10 photos each participant, 8 removed

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Appendix Table 5 – *continued from previous page*

Ref.	Dataset	Description
[99]	~90 heavy metal solution spectra	10 spectra each, lead, zinc, copper solutions with 500, 1000, 2000 mg/L concentrations
[175]	90 Yinhuang solution spectra	Modeling: 45 spectra (mean of 3 spectra per sample, 45 Yinhuang oral solutions with 1, 2.5, 4, 5, 6.5 mg/mL of Baicailin) Testing: 45 spectra (mean of 3 spectra per sample, 45 Yinhuang oral solutions with 2, 3.5, 4.6, 6 mg/mL of Baicailin)
[185]	75 blood glucose spectra	26 participants, train/test split: 60/15
[81]	70 blood glucose measurements	1 measurement per participant, 70 participants
[144]	60 weed spectra	10 spectra per species, 6 weed species
[5]	54 spectra	3 scans per sample, 18 samples
[116]	51 blood glucose measurements	89 participants, fasting conditions between 8 hours no eat and 4 hours after eat, 38 data points excluded due to low quality
[140]	45 liquid spectra	12 spectra of blue dyes (0, 0.001%, 0.01%, 0.05%), 15 spectra of 5 milk solutions (pure milk, 2 ml detergent, 1.5 g salt, 1.5 g starch, 2 ml water in 20 milk), 18 spectra of 6 alcohol solutions (100%, 80%, 60%, 40%, 20%, 0% rum in water)
[34]	40 vein images	5 images per participant, 8 participants
[102]	30 oil spectra	5 oil samples with 0.2, 0.3, 0.4, 0.5, 0.6 w/w% concentrations
[4]	26 cell images	13 cancer cells, 13 control cells)
[125]	20 milk spectra	10 spectra per sample, 2 milk samples, 0%, 25% water
[180]	16 arterial voluntary contraction measurements	4 participants, arterial occlusion and isometric voluntary forearm muscle contraction, maximum voluntary contraction at 10%, 30%, 50% and 100%
[171]	10 tea measurements	10 tea samples
[60]	X snow block measurements	with orientational and spatial variability
[3]	X spectra	45 samples from 4 component categories
[150]	X records	20 participants, 5 events
[66]	X fNIRS+EEG records	1 participant, Oxford Sleep Resistance Test, 20 times each task
[24]	X spectra	282 samples
[189]	X records	20 participants with 19 elderly and one 38 age-matched controls

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Appendix Table 5 – *continued from previous page*

Ref.	Dataset	Description
[107]	X records	6 participants
[10]	X spectra	300 samples
[156]	X records	20 participants
[166]	X records	13 students + 9 experts
[128]	X fNIRS records	12 participants, 6 repeated reading experiments per participants
[89]	X fNIRS records	20 participants, basketball dribbling 16 times for ~10 sec while sitting on a chair
[157]	X fNIRS records	10 participants 5 test sets per participant, 10 trials each test set, 1 task each trial (thinking yes or no), 10 sec rest inbetween
[133]	X fNIRS records	7 participants, 4 tasks per session, 3 sessions
[91]	X fNIRS records	5 trials per task, 4 participants
[87]	X fNIRS records	36 participants, 15, 10, 11 for 3 groups of lower extremity burn, upper extremity burn, healthy, walking-related
[141]	X fNIRS records	6 participants, 4 sessions each participant, cognitive tasks
[16]	X leaf spectra	15 leaves per tree, 6 trees, per week
[6]	X cereal spectra	80%/20% for train/test, 164 breakfast cereal samples, 1 g cereal was mixed with 40 mL of 80% (v/v) ethano
[54]	X blood glucose spectra	45 samples from 5 participants, Glucose levels 70 - 140 mg/dL
[186]	X corn leaf spectra	38 plant samples, with 19 of high N plants and 19 of low N plants
[101]	X food spectra	3 samples for 8 foods, scanned at day x, $0 \leq x \leq 30$, x varies among samples
[80]	X glucose and bilirubin solution spectra	In vitro: total number unspecified (22 glucose solutions with 0 - 800 mg/dL concentrations, 15 bilirubin solutions with 2 - 30 ml/dL concentrations). In vivo: 24 data points (19/5 data points for train/test, 24 participants)
[44]	X fNIRS records	25 participants, 36 blocks in 3 tasks
[49]	X hand vein images	hand vein images from 20 participants
[13]	X forage spectra	612 alfalfa, 516 grass samples, using 3 mobile NIRS and 1 benchtop NIRS
[76]	X iron(II) and phosphate solution spectra	Modeling: total number unspecified (standard iron(II) and phosphate solutions with 0 - 5 mg/L concentrations respectively) Testing: 25 data points (5 data points per solution, 5 standard iron(II) and phosphate solutions with 0.05, 0.1, 1, 2, 3 mg/L concentrations, respectively)

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Appendix Table 5 – *continued from previous page*

Ref.	Dataset	Description
[129]	X fNIRS records	19 participants, all right-handed, 8 blocks of working memory tasks per participant
[123]	X distance and relative body orientation measurements	64 participants, with 16 teams of 4 participants, 4 task roles, 6 task timelines

X – total number unspecified.

Appendix C CRITERIA FOR REGRESSION TASKS

We show the equations of different criteria for regression tasks below

Mean absolute error (MAE)	$MAE = \sum_{i=1}^{N} \lvert y_i - \hat{y}_i \rvert$
Root mean square error (RMSE)	$RMSE = \sqrt{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}$
Root relative squared error (RRSE)	$RRSE = \sqrt{\frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \overline{y})^2}}$
Standard error of prediction (SEP)	$SEP = \sqrt{\frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{N}}$
Mean percentage error (MPE)	$MPE = \frac{100\%}{N} \sum_{i=1}^{N} \frac{y_i - \hat{y}_i}{y_i}$
Mean squared error (MSE)	$MSE = \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$
Coefficient of determination	$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \overline{y}_i)^2}$

where $\hat{y}_i$, y_i, and $\overline{y}$ represent an estimated value, a ground-truth value, the mean of ground-truth values respectively.

Appendix D MOBILE NEAR-INFRARED SENSING REGRESSION TASKS

We provide a comprehensive list of regression tasks and corresponding machine learning models for recent studies using mobile NIR technologies. We note that a paper can include multiple tasks. For analysis, please refer to Section 6.2.

Appendix Table 6. Regression tasks using NIR methods in recent studies, sorted by tasks.

Ref.	Task	Model	Datatype	Performance
[125]	Added water estimation	SLR	Spectra	MAE<1%
[140]	Alcohol concentration prediction	MLP	Spectra	RMSE=2.84, RRSE=7.87%
[175]	Baicailin concentraion prediction	PLS	Spectra	$R^2 = 0.9920, SEP = 87.7 \mu g/mL$
[80]	Bilirubin concentration prediction	SLR	Spectra	R^2=0.272 for transmittance, 0.4336 for reflectance
[36]	Biochemical variables prediction	RoBoost-PLS regressor	Images	$R^2 2$ = 0.990, 0.848, 0.927, RMSE = 3.14, 10.20, 7.58 g/L, for Syrah, Fer, Mauzac, respectively
[80]	Blood glucose prediction	SLR	Spectra	MPE=8.27%, RMSE=18.52 mg/dL
[116]	Blood glucose prediction	MLP	Values	MAE=5.855 mg/dL
[119]	Breast milk content prediction	PLS regressor	Spectra	R^2 = 0.85, 0.67, 0.01 for fat, raw protein, carbohydrates, respectively
[155]	Curcuminoid prediction	PLS	Spectra	R^2 = 0.797, RMSE=0.306
[82]	Drink sucrose concentration prediction	MLR	Spectra	$RMSE \leq 2.0 g/100 ml$
[140]	Dye concentraion prediction	MLP	Spectra	RMSE=4.29, RRSE=14%
[75]	Food nutrient concentration prediction	RF regressor	Spectra	RMSE = 1.87 $g/100 ml$
[24]	Fructose / glucose / sucrose concentration prediction	PLS-OPS regressor	Spectra	RMSE = 15.90, 1.18, 1.65 mg/ml using DSJ, RMSE = 23.23, 1.40, 2.08 mg/ml using LSJ, for sucrose, glucose, fructose, respectively.
[82]	Glucose and fructose concentration prediction	MLR	Spectra	$RMSE \leq 2.29 g/100 ml$
[79]	Glucose concentration prediction	DT	Spectra	R^2=0.96, MSE=0.021
[80]	Glucose concentration prediction	SLR	Spectra	R^2=0.5214 for transmittance, 0.5449 for reflectance
[185]	Inter-subject blood glucose prediction	ELM-TrAdaBoost	Spectra	RMSE=0.137, R^2=0.9660
[76]	Iron(ii) concentration prediction	SLR	Spectra	Mean % Bias=0.93%, Mean % R.S.D.=3.44%
[82]	Liquid dilution percentage prediction	MLR	Spectra	$RMSE$ = 2.09, 0.50, 1.19 for diluted liquor, milk, perfume, respectively

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Appendix Table 6 – *continued from previous page*

Ref.	Task	Model	Datatype	Performance
[56]	Live and dead tissue estimation	MLP	Spectra	R^2=0.77, MSE=106.25
[169]	Maturity level prediction	PLS	Spectra	R^2 = 0.83, RMSE=1.52, 5-fold
[178]	Milk total solids estimation	PLS	Spectra	RMSE=0.27% and 0.21% for raw and homogenized milk respectively
[67]	Nitrogen content prediction	RQGPR	Spectra	R^2=0.7396, RMSE=1.13, MAE=0.72
[5]	Nitrogen prediction	RF regressor	Spectra	R^2 = 0.661, RMSE = 0.022
[170]	Nutrition content prediction	PLS	Spectra	RMSE=0.0952, 0.0771, 0.0373 mg/g for Chl-a, Chl-b, Car, respectively
[142]	Nutritive parameters prediction	PLS	Spectra	R^2=0.516, 0.742, 0.704 for crude protein, acid detergent fibre, neutral detergent fibre, respectively
[153]	Phenolic compounds prediction	PLS regressor	Spectra	R^2_{CV} > 0.89 for all phenolic compounds
[76]	Phosphate concentration prediction	SLR	Spectra	Mean % Bias=0.73%, Mean % R.S.D.=1.25%
[5]	Phosphor prediction	RF regressor	Spectra	R^2 = 0.705, RMSE = 9.250
[38]	Plasticiser design points prediction	PLS	Spectra	no metric computed
[5]	Potassium prediction	Gradient-Boost regressor	Spectra	R^2 = 0.774, RMSE = 6.711
[139]	Predicting moisture content in c. oleifera seeds	PLS regressor	Spectra	R^2 = 0.927, SEP = 0.848%db with backward interval wavelength selection
[8]	Predicting rice adulteration level	MLP regressor	Spectra	R^2 >= 0.95
[7]	Protein quality prediction	PLS	Spectra	$R^2 \geq 0.92$, RMSE$\leq$ 3.07%
[118]	Pupil center estimation	MLP	Images	pixel error=1.2
[118]	Pupil size estimation	MLP	Images	pixel error=0.85
[46]	Soil nitrogen prediction	PLS	Spectra	R^2 = 0.934, RMSE=1.923, relative error< 13% for in situ test
[191]	Soil nitrogen prediction	SVM	Spectra	RMSE=0.0193 g/kg
[6]	Sugar content prediction	PLS	Spectra	$R^2 \geq 0.93$, SEP$\leq$2.4 g/100 g
[127]	Sugarcane quality prediction	PLS	Spectra	R^2=0.86, 0.84, 0.80, 0.88, 0.81, RMSE=0.84, 0.83, 0.87, 1.22, 1.60, for FS, CJ, RJ, SCS, SS, respectively

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Appendix Table 6 – *continued from previous page*

Ref.	Task	Model	Datatype	Performance
[171]	Tea polyphenols concentration prediction	SLR	Values	R^2 = 0.99948
[62]	Tobacoo chemical composition prediction	PLS	Spectra	R^2=0.96, 0.91, 0.92, 0.90, $RMSE$ =1.29, 1.35, 0.08, 0.14, for total sugar, reducing sugar, total nitrogen, nicotine, respectively
[67]	Water content prediction	RQGPR	Spectra	R^2=0.4608, RMSE=3.97, MAE=2.75

Appendix E MOBILE NEAR-INFRARED SENSING CLASSIFICATION TASKS

We provide a comprehensive list of classification tasks and corresponding machine learning models for recent studies using mobile NIR technologies. For analysis, please refer to Section 6.3.

Appendix Table 7. Classification tasks using NIR methods in recent studies, sorted by tasks.

Ref.	Task	Model	Datatype	Performance
[157]	Affirmative-negative brain activity discrimination	MLP	fNIRS records	accuracy = 0.7
[101]	Aging day recognition	J48	Spectra	accuracy > 0.887
[101]	Bacteria level recognition	J48	Spectra	accuracy = 0.973, 0.966, 0.760 for beef, pork, bass, respectively
[98]	Bottle recognition	SVM	Spectra	accuracy = 0.656
[26]	Brain activity classification	BNN	Spectra	accuracy = 0.8314, 0.8047 for with and without proposed technique repsectively
[115]	Breathing condition classification	RF	fNIRS records	accuracy = 0.87, F1-score = 0.86
[44]	Cogeo and noneo classification	SVM	fNIRS records	accuracy = 0.77
[162]	Cognitive fatigue detection	RF	fNIRS records	accuracy = 0.7091, F-score = 0.7027
[130]	Daily-living action recognition	SVM	fNIRS records	accuracy = 0.7
[136]	Diseased plant recognition	XY-F	Spectra	accuracy = 0.9516
[39]	Dorsal and palmar recognition	MC	Images	EER=7.52
[82]	Drink recognition	kNN / SVM / RF	Spectra	accuracy = 1.0 for all
[66]	Drowsy state classification	SVM	fNIRS records	accuracy = 0.659
[98]	Ethanol solution recognition	HESCA / PLS	Spectra	accuracy = 0.965 for both
[124]	Food freshness recognition	CNN	Spectra	accuracy = 0.85 for salmon, 0.88 for tuna, 0.92 for beef
[182]	Food powder recognition	CNN	Spectra	accuracy = 1.0
[183]	Food powder recognition	SVM	Spectra	accuracy = 1.0
[184]	Food powder recognition	SVM	Spectra	accuracy = 1.0
[153]	Genetically modified crops classification	SVM	Spectra	accuracy = 1.0
[64]	Gesture recognition	LDA	fNIRS records	accuracy> 95%

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Appendix Table 7 – *continued from previous page*

Ref.	Task	Model	Datatype	Performance
[83]	Gluten-free wrap recognition	SVM	Spectra	accuracy = 0.858
[135]	Hand identification	DT	Images	accuracy = 0.9444
[72]	Iris segmentation and recognition	CNN	Images	EER=7.41%, $OP_{0.01}$ = 50.02%, ME=0
[92]	Mango maturity index classification	PLS	Spectra	accuracy = 0.957
[169]	Maturity level classification	SVM	Spectra	accuracy = 0.83, F1=0.89, 10-fold
[98]	Methanol solution recognition	SVM	Spectra	accuracy = 0.864
[140]	Milk solution recognition	MLP	Spectra	F-score=0.785
[93]	Pill recognition	NB	Spectra	accuracy = 1.0, with 10-fold cross valiation
[28]	Pill recognition	SVM	Spectra	accuracy = 0.8889
[93]	Pill recognition scanned by non-experts	RF	Spectra	accuracy = 0.9625
[1]	Ripe apple recognition	DT	Spectra	accuracy = 0.671
[148]	Root-knot nematode infection detection	NB	Spectra	accuracy = 0.82
[123]	Task role recognition	RF	Values	accuracy = 0.849
[123]	Task timeline recognition	RF	Values	accuracy = 0.932
[91]	Task-rest brain status recognition	SVM	fNIRS records	accuracy = 0.7
[101]	Thiobarbituric acid (tba) recognition	J48	Spectra	accuracy = 0.993, 0.967, 0.947 for beef, pork, bass, respectively
[58]	Vein biometric recognition	PIS-CVBR	Images	EER=14.76%, 17.03%, for Pocophone F1, Mi 8, respectively
[101]	Volatile basic nitrogen (vbn) recognition	J48	Spectra	accuracy = 0.980, 0.973, 0.893 for beef, pork, bass, respectively
[10]	Watermelon ripeness classification	KNN	Spectra	accuracy = 0.907

Appendix F MOBILE NEAR-INFRARED APPLICATIONS

We provide a comprehensive list of applications for recent studies using mobile NIR technologies. For application analysis, please refer to Section 7.1.

Appendix Table 8. Applications using NIR technologies in recent studies, sorted by application area.

Ref.	Area	Use case	NIR technology
[92]	Agriculture	Classifying mango maturity index	NIRS
[136]	Agriculture	Detecting plant infection	VIS-NIRS
[191]	Agriculture	Estimating soil nitrogen and moisture	NIRS
[46]	Agriculture	Estimating soil nitrogen	NIRS
[1]	Agriculture	Estimating fruit quality	NIRS
[56]	Agriculture	Assessing berry cell vitality	NIRS
[169]	Agriculture	Estimating fruit maturity levels	NIRS
[24]	Agriculture	Estimating sugar concentration of sugarcane juice	NIRS
[127]	Agriculture	Estimating sugarcane quality	VIS-NIRS
[148]	Agriculture	Detecting crop disease	NIRS
[171]	Agriculture	Detecting tea polyphenol for quality control	NIR sensing
[153]	Agriculture	Analyzing genetically modified crops	NIRS
[164]	Agriculture	Estimating leaf chlorophyll density	VIS-NIRS
[36]	Agriculture	Predicting biochemical variables of grape berries	NIR imaging
[62]	Agriculture	Detecting tobacoo chemical composition	NIRS
[52]	Agriculture	Assessing thermal defoliation of cottons	VIS-NIRS
[13]	Agriculture	Analyzing dairy farm forage quality	NIRS
[10]	Agriculture	Estimating watermelon ripeness	NIRS
[170]	Agriculture	Onsite nutritional diagnosis of tea plants	NIRS
[67]	Agriculture	Estimating left nitrogen and water contents in crops	NIRS
[139]	Agriculture	Predicting moisture content in C. oleifera seeds	NIRS
[144]	Agriculture	Identifying weed in rice farming	VIS-NIRS

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Appendix Table 8 – *continued from previous page*

Ref.	Area	Use case	NIR tech
[5]	Agriculture	Predicting soil contents of nitrogen, phosphor, and potassium	NIRS
[186]	Agriculture	Analyzing corn leaves	NIRS
[7]	Agriculture	Screening soybean quality	NIRS (FT-NIR)
[142]	Agriculture	Analyzing dairy farm forage quality	NIRS
[31]	Agriculture	Analyzing dairy farm forage quality	NIRS
[16]	Agriculture	Analyzing citrus plant leaves as proximal sensors for remote sensing	VIS-NIRS
[51]	Agriculture	Analyzing dairy farm forage quality	NIRS
[86]	Environmental	Analyzing microalgae in freshwater	VIS-NIRs
[3]	Environmental	Analyzing glyphosate residues in waters	NIRS
[60]	Environmental	Estimating snow optically equivalent diameter (OED)	NIR sensing
[147]	Environmental	Analyzing macrophyte species as proximal sensors for remote sensing	VIS-NIRS
[71]	Environmental	Localizing bats	NIR imaging
[99]	Environmental	Monitoring heavy metals in water as proximal sensors for remote sensing	VIS-NIRS
[8]	Food computing	Predicting rice adulteration levels as fraudulent products	NIRS
[83]	Food computing	Detecting gluten in bread	NIRS
[82]	Food computing	Estimating content concentration and identifying everyday drinks	NIRS
[184]	Food computing	Classifying food powders	VIS-NIRS
[119]	Food computing	Analyzing breast milk contents	NIRS
[75]	Food computing	Analyzing food nutrients	NIRS
[178]	Food computing	Detecting milk composition	VIS-NIRS
[6]	Food computing	Monitoring sugar content in breakfast cereals	NIRS (FT-NIR)

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Appendix Table 8 – *continued from previous page*

Ref.	Area	Use case	NIR tech
[124]	Food computing	Estimating freshness of salmon, tuna and beef	VIS-NIRS
[155]	Food computing	Estimating curcuminoids in turmeric powder	NIRS
[183]	Food computing	Classifying food powders	VIS-NIRS
[98]	Food computing	Detecting counterfeit alcohols	UV-VIS-NIRS
[140]	Food computing	Analyzing liquid food	Photoacoustic
[182]	Food computing	Classifying food powders	VIS-NIRS
[125]	Food computing	Detecting milk adulterations	NIRS
[76]	Food computing	Analyzing liquid contents	NIRS
[101]	Food computing	Estimating freshness of meat, fish, vegetable and fruits	NIRS
[126]	Food computing	Estimating fat in food	NIRS
[123]	HCI	Measuring interaction proxemics in social activities	NIR sensing
[165]	HCI	Brain-machine interface	fNIRS (EEG-fNIRS)
[150]	HCI	Analyzing brain activities during driving in winter	fNIRS
[177]	HCI	Estimating cybersickness in VR based on brain activity monitoring	fNIRS
[180]	HCI	Monitoring muscle activity for gesture recognition	fNIRS
[43]	HCI	Embedding interactive tags into 3D prints	NIR imaging
[156]	HCI	Analyzing brain activities before and after take-over request in automated driving	fNIRS
[89]	HCI	Monitoring hemodynamic response in brain during basketball dribbling	fNIRS
[64]	HCI	Monitoring muscle activity for gesture recognition	fNIRS (sEMG+fNIRS)
[167]	HCI	Detecting pupil and glint	NIR imaging
[157]	HCI	Brain-machine interface	fNIRS
[174]	HCI	Gesture recognition	NIR imaging
[118]	HCI	Eye-tracking	NIR imaging

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Appendix Table 8 – *continued from previous page*

Ref.	**Area**	**Use case**	**NIR tech**
[77]	HCI	Controlling home appliances	NIR communications
[91]	HCI	Brain-machine interface	fNIRS
[130]	HCI	Brain-machine interface	fNIRS
[106]	HCI	Eye-tracking	NIR imaging
[68]	HCI	Brain imaging for action analysis	fNIRS
[26]	Healthcare	Brain imaging for action analysis	fNIRS
[152]	Healthcare	Monitoring hemodynamic response in brain	fNIRS
[115]	Healthcare	Classifying breathing conditions (baseline, loaded, rapid)	fNIRS
[189]	Healthcare	Investigating memory-related prefrontal cortex activity in elderly with diabetes	fNIRS
[49]	Healthcare	Imaging dorsal hand veins with different skin tones	NIR imaging
[151]	Healthcare	Monitoring oxygenation in brain (cerebral oximetry)	fNIRS
[81]	Healthcare	Monitoring glucose in blood	NIR sensing
[55]	Healthcare	Monitoring blood oxygen and heart rate	NIR sensing (PPG)
[88]	Healthcare	Photo therapy for hyper-pigmentation	NIR radiation
[176]	Healthcare	Analyzing falsified drugs	NIRS
[107]	Healthcare	Detecting muscle fatigue	fNIRS
[122]	Healthcare	Detecting bladder filling to capacity	NIR sensing
[97]	Healthcare	Monitoring glucose in blood	NIR sensing
[34]	Healthcare	Vein imaging for intravenous access	NIR imaging
[100]	Healthcare	Monitoring hemodynamic response in brain	fNIRS
[33]	Healthcare	Monitoring glucose and insulin in blood	NIRS
[23]	Healthcare	Monitoring blood oxygen and heart rate	NIRS
[80]	Healthcare	Monitoring glucose and bilirubin in blood	NIRS

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Appendix Table 8 – *continued from previous page*

Ref.	Area	Use case	NIR tech
[79]	Healthcare	Estimating glucose in blood based on saliva samples	NIRS
[181]	Healthcare	Brain imaging	fNIRS
[129]	Healthcare	Monitoring prefrontal activity for daily use	fNIRS
[93]	Healthcare	Identifying pharmaceuticals	NIRS
[28]	Healthcare	Identifying pharmaceuticals	NIRS
[12]	Healthcare	Assessing sleep apnea	NIRS
[185]	Healthcare	Monitoring glucose in blood	NIRS
[30]	Healthcare	Detecting breast tumor	NIR imaging
[146]	Healthcare	Monitoring hemodynamic response in brain	fNIRS
[188]	Healthcare	Monitoring oxygenation in brain (cerebral oximetry)	fNIRS
[111]	Healthcare	Estimating blood pressure	NIR sensing (PPG)
[21]	Healthcare	Monitoring glucose in blood	NIR sensing
[47]	Healthcare	Detecting extravasation during injection	NIRS
[2]	Healthcare	Monitoring hemodynamic response in brain	fNIRS
[175]	Healthcare	Identifying pharmaceuticals	NIRS (AOTF-NIR)
[37]	Healthcare	Monitoring blood oxygen and heart rate	NIRS
[172]	Healthcare	Monitoring hemodynamic response in brain	fNIRS
[116]	Healthcare	Monitoring glucose and bilirubin in blood	NIR sensing (PPG)
[54]	Healthcare	Monitoring glucose in blood	NIRS (BIS-NIRS)
[57]	Healthcare	Intraoperative guidance for surgery	NIR fluorescence imaging
[50]	Healthcare	Diagnosing breast cancer	NIRS
[145]	Healthcare	Brain imaging	fNIRS
[20]	Healthcare	Monitoring hemodynamic response in brain for pigmented subjects	fNIRS
[131]	Healthcare	Intraoperative preservation of parathyroid glands	NIR imaging

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Appendix Table 8 – *continued from previous page*

Ref.	Area	Use case	NIR tech
[87]	Healthcare	Investigating cortical brain activity during usual walking in patients with neurological injury	fNIRS
[17]	Healthcare	Monitoring hemoglobin and water concentration detection in human body	fNIRS
[149]	Healthcare	Monitoring regional hemoglobin oxygen	fNIRS
[161]	Healthcare	Monitoring glucose in blood	NIRS
[4]	Healthcare	Detecting colorectal cancer cells	NIR fluorescence imaging
[44]	Psychology	Onset classification for working memory tasks	fNIRS
[166]	Psychology	Analyzing brain's microstates during surgical tasks	fNIRS
[141]	Psychology	Monitoring hemodynamic response in brain during cognitive tasks	fNIRS
[66]	Psychology	Monitoring drowsiness	fNIRS+EEG
[162]	Psychology	Detecting cognitive fatigue	fNIRS
[128]	Psychology	Estimating index of fatigue	fNIRS
[117]	Psychology	Measuring anxiety index	fNIRS
[108]	Psychology	Monitoring hemodynamic response in brain during sleep in relation to stress	fNIRS
[133]	Psychology	Estimating cognitive performance	fNIRS
[69]	Security	Multi-band photographing for security and surveillance	RGB-NIR imaging
[58]	Security	Imaging veins for biometric recognition	NIR imaging
[135]	Security	User identification using hand geometrical features	NIR imaging
[72]	Security	Recognizing iris	NIR imaging
[39]	Security	Imaging vascular pattern of hand-veins for biometric recognition	NIR imaging
[103]	Security	Labelling objects invisibly for privacy protection	NIR imaging
[65]	Security	Detecting relay attacks	NIR sensing (communication)

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Appendix Table 8 – *continued from previous page*

Ref.	**Area**	**Use case**	**NIR tech**
[38]	Other	Analyzing solid rocket propellant chemical and structural health status	NIRS
[59]	Other	N/A (a design for mobile NIRS prototype)	NIRS
[32]	Other	Monitoring vocal fold vibration	NIR sensing (Photoglottography)
[102]	Other	Analyzing transformer oil inhibitor contents	NIRS
[158]	Other	Analyzing conservation and restoration of paper-based artifacts	NIR imaging
[173]	Other	Underdrawing identification for large paintings	NIR imaging