

A Survey on Computer Vision for Assistive Medical Diagnosis From Faces

Jérôme Thevenot^{ID}, Miguel Bordallo López^{ID}, and Abdenour Hadid^{ID}

Abstract—Automatic medical diagnosis is an emerging center of interest in computer vision as it provides unobtrusive objective information on a patient’s condition. The face, as a mirror of health status, can reveal symptomatic indications of specific diseases. Thus, the detection of facial abnormalities or atypical features is at utmost importance when it comes to medical diagnostics. This survey aims to give an overview of the recent developments in medical diagnostics from facial images based on computer vision methods. Various approaches have been considered to assess facial symptoms and to eventually provide further help to the practitioners. However, the developed tools are still seldom used in clinical practice, since their reliability is still a concern due to the lack of clinical validation of the methodologies and their inadequate applicability. Nonetheless, efforts are being made to provide robust solutions suitable for healthcare environments, by dealing with practical issues such as real-time assessment or patients positioning. This survey provides an updated collection of the most relevant and innovative solutions in facial images analysis. The findings show that with the help of computer vision methods, over 30 medical conditions can be preliminarily diagnosed from the automatic detection of some of their symptoms. Furthermore, future perspectives, such as the need for interdisciplinary collaboration and collecting publicly available databases, are highlighted.

Index Terms—Computer vision, face analysis, facial symptoms, imaging, medical diagnosis.

I. INTRODUCTION

THE global increase in life expectancy within the world population during the past century has been possible as a result of the improved access to clinical facilities and developments in medical diagnostics. To further enhance diagnosis with an objective second assessment, computer-based solutions have recently been developed to help in the early detection of some diseases. In addition, as a result of the expansion of the human lifespan and its quality, the boost of clinical needs induces high costs for the society. These costs are suitable to be reduced with the inclusion of automatic processes. Vision is a key component

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J. Thevenot is with the Medical Imaging, Physics and Technology Research Unit and the Center for Machine Vision and Signal Analysis, University of Oulu, Oulu 90014, Finland (e-mail: jerome.thevenot@oulu.fi).

M. B. López and A. Hadid are with the Center for Machine Vision and Signal Analysis, University of Oulu, Oulu 90014, Finland (e-mail: miguelbl@ee.oulu.fi; hadid@ee.oulu.fi).

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for building artificial systems that can perceive and understand their environment, similarly to humans who perceive the great majority of information about their environment through sight. During the past decade, there have been numerous research and development efforts in the field of wearable health monitoring systems that were motivated by the need to monitor a person’s health status outside of the hospital [1]. However, most proposed techniques for health monitoring require users to attach bulky sensors, chest straps or sticky electrodes. This obviously discourages regular use because the sensors can be uncomfortable or encumbering. To confront these issues, the development of non-contact healthcare has increased, along with technologies robust and simple to use for the diagnostic of conditions and the follow-up of patients [2], [3]. Camera-based methods offer an unobtrusive solution for the monitoring and diagnosis of subjects. Recording devices such as web cameras or smartphones are nowadays common tools, providing an easy access solution of any physiological measurements reachable by such technologies.

The human face houses most of the sensory apparatus – eyes, ears, mouth, and nose – allowing the bearer to see, hear, taste, and smell. Apart from these biological functions, it also provides several signals about health. Indeed, certain medical conditions alter the expression or appearance of the face due to physiological or behavioral responses. These facial signs of disease can provide information to the clinician concerning the state of the patient. From a computer vision viewpoint, detecting abnormalities in patient facial structures and/or expressions is a challenging research problem. The critical issues concern the establishment of basic understanding of the correlations between the face symptoms and the health conditions and to the development of computational models that encode the identified correlations. The main issue is the lack of a code-book, which maps the range of facial patterns to clinical conditions based on proven medical evidences (e.g., indicating that many diseases and brain disorders produce facial abnormalities and interrupt normal facial expression).

Establishing the relationship between digital images and clinical information is a challenging task that can be overcome by detecting medical symptoms. For example, a multitude of genetic syndromes can cause craniofacial abnormalities that can eventually come in pairs with a defect on other organs or systems [4]. While some of these syndromes can have very distinctive facial features, others can be harder to detect at first sight. The study of facial morphology is highly interesting when it concerns the discrimination of craniofacial pathologies,

requiring for this purpose the establishment of robust facial landmarks [5]. Furthermore, considerations on how to define a normal face [6] from a point of view of aesthetic and social interactions have generated multiple studies to characterize facial morphological features such as facial symmetry or skin color. While evaluating craniofacial abnormalities is straightforward by comparing anatomical measurements of a subject with the ones of an average healthy individual, the facial diagnostic of other conditions can be more challenging. Furthermore, clinicians provide a subjective assessment which can vary among the practitioners, and be influenced by the ethnic background of the patient [7]. For this purpose, recent literature has exposed the apparition of new technologies as well as the development of image processing tools to capture the required data, essential for clinical assessment of health conditions in a subjective manner. The main idea behind using computer vision for a clinical purpose would be to decrease the errors related to human factor in the decision-process regarding patients. Furthermore, while medical examinations are costly, analysis based on facial imaging remain low-cost and their developments could eventually lead to a reduction of healthcare expenditures.

The aim of this article is to provide the reader with an overview of the research problem with references to existing works, to stimulate the research and to help unifying the efforts towards the development of new tools and databases for evaluating and monitoring the progress in the field. In this regard, this article can be used as a reference of both experienced and non-experienced researchers. Only distant non-invasive imaging modalities available to the public were chosen, to provide reproducible studies for research groups without access to expensive or encumbering medical equipment such as magnetic resonance imaging or computed tomography. This survey article presents a general overview of different works in the literature on using computer vision for health diagnosis from faces. It also discusses the open issues and future directions. The focus is not only on conventional sensing technologies (e.g., digital imaging) but also on novel imaging methods such as thermography or stereo-photogrammetry. From this survey, the reader will get an understanding of the challenges inherent of the detection of different medical conditions and how they have been tackled so far. Eventually, some leads for new research based on alternative approaches or combination of existing ones could be inspired from this review.

The article is organized as follows. An overview of the different imaging techniques, their particularities and limitations is described in Section II. Section III gives a typical description of the methodological workflow of the facial analysis process. Section IV provides a brief description of the facial anatomy. Section V reports specific medical conditions with computer-assisted solutions. This non-exhaustive list attends to present the different options available for an automatic diagnostic approach. The main findings and references are summarized in Section VI. Section VII discusses the significance of the findings, and provides futures perspectives and requirements of computer-based diagnostics of medical conditions from facial imaging, while Section VIII concludes the article.

II. FACIAL IMAGING MODALITIES

The nature of the imaging data can be diverse depending on relevant facial features to assess and the aim of the study. While conventional options such as basic digital imaging or video have been widely used, some alternative options have emerged to collect further information. The continuous reduction of costs for new imaging devices, as well as the late development of new tools in image processing, have further encouraged the studies of these alternative solutions [8], [9]. This section briefly introduces the possibilities in terms of facial imaging modalities, with a short description of their strengths to detect specific symptomatic clues.

Conventional digital cameras can encode the visible light in three different channels, (red, green and blue). As the most common option for assessment of skin color [10] and facial morphology [11], the ability of conventional digital imaging to discriminate specific health conditions has been extensively studied. However, one drawback of two-dimensional imaging applied to facial morphology is its inaptitude to provide depth of the anatomical landmarks, an issue solved using stereo photogrammetry [12].

The technique of stereo photogrammetry consists in generating a three-dimensional surface from a set of images acquired from different locations. Multiple images are combined through computational models to estimate the actual 3D position of the scanned environment. This approach permits to obtain 3D coordinates of object points from triangulation and reconstructing its volume from them, allowing accurate volumetric distance measurements. Due to its spatial accuracy, this technique has been largely used in studies of craniofacial deformities [13], since an accurate volumetric delimitation of facial edges can be obtained. Following this trend, extensive research has been performed to represent the face volumetrically [14], capturing subtle information of conditions (e.g., schizophrenia) [15]. The recent introduction of low-cost depth cameras (e.g., Microsoft Kinect 1&2) provides exciting new opportunities for detailed facial image analysis. For example, the study of Nakamura *et al.* [16] used low-cost depth camera to grade torticollis severity from the patient's facial direction and tilt. Furthermore, these sensors have already been applied in clinical applications related to reeducation and therapeutic exercises [17].

Video cameras allow the recording of the temporal variations of a scanned environment, enabling the assessment of small movements or color variations, even when they are unperceivable by the human eye. Videos are necessary for specific conditions related to motion or presenting symptoms solely perceived over a certain period. For example, multiple studies related to eye tracking have been performed to correlate visual behaviors with psychiatric [18] or anxiety disorders [19]. However, while video imaging provides more information than basic digital imaging, the nature of the data remains very similar.

There is an increase of studies using imaging modalities focusing on a different spectral range than the conventional visible one, providing new leads of research. As one of them, thermal imaging is a non-contact, non-invasive imaging method which provides information on human body temperature by assessing

the infrared spectrum of the subject. Thermal cameras can detect radiation in the infrared range of the electromagnetic spectrum, usually from 0.9 to 20 μm , converting the amount of radiation into visible images. Since infrared radiation is directly proportional to the temperature emitted by all entities, thermal images make it possible to see objects even without visible illumination. The nature of the information provided by this method makes it highly relevant for applications related to clinical medicine [20]. Indeed, not only the thermal-print provides information on the shape of the face [21], but also multiple contributing thermal factors can be assessed (e.g., blood flow, cell metabolism, sweat gland activation), causing local changes in superficial skin temperature. More specifically, different reasons such as inflammatory processes [22], fever [23], [24], cancers [25] or even medications [26] can be responsible for changes in the skin temperature. Due to the increase of thermal camera accuracy and resolution [27], research has been performed lately to evaluate how much information the distribution of heat in the face can provide. For example, various applications related to mass-screening have been using thermal imaging as a fever detection tool [28] for severe acute respiratory syndrome related to H5N1 or more recently to Ebola virus.

III. COMPUTER VISION METHODOLOGY FOR FACIAL ANALYSIS

The computer vision methodology applied in assistive medical diagnosis typically follows a similar structure: it relies on the extraction and combination of several face descriptors obtained from pre-processed images and uses them to build models that can generalize to unseen data. These features, extracted both in the spatial and spatio-temporal data, are then input into classifiers to predict if the new sample is of a certain type (classification) or to assess the severity of a symptom or condition in a continuous way (regression).

As preprocessing, the first step of most computer vision techniques consists in segmenting specific regions of interest from each sample and detecting either faces or landmarks. The regions containing the useful facial information are cropped and registered into a predefined template, usually preserving the interpupillary distance (used as reference). The selection of useful information is derived from the location of the symptoms to evaluate. For example, studies on facial abnormalities will focus on regions known to be affected and will compare morphological measures with the ones expected in “healthy” subjects. An eventual secondary step in preprocessing is the conversion of the colorspace, either to reduce the complexity of the model by using solely grayscale values if sufficient, or to enhance specific color-based features if necessary (eg. studies related melanoma, hepatitis, etc.).

Local descriptors based on texture analysis such as variants of Histograms of Oriented Gradients (HOG) [29] or Local Binary Patterns (LBP) [30], have also been extensively exploited as they can evaluate local characteristics that can be affected by the medical condition. A typical methodology used with hand-crafted features encodes the face information by dividing each frame into blocks and extracting multiscale features from the

ones within the regions of interest of the studied disease, concatenating the results into a high dimensional descriptor to exploit multiple information simultaneously. However, since this combination generates very large feature vectors, dimensionality reduction techniques have been extensively used. Among the most used methods are Principal Component Analysis (PCA), Independent component Analysis (ICA), or variations that try to learn the weight of each feature component.

The next step after feature extraction is the classification, with complexity of methods varying based on the discriminative power of the features. Cosine similarity and K-Nearest-Neighbors have been used with mixed performance, while model-based classification utilizing a bi-class support vector machine (SVM), shows to be the preferred method when the amount of data allows the partition into meaningful splits of training and testing data. As the result of the analysis, the post-processing provides the “final verdict” on the medical condition targeted and can eventually show which features suggested the decision, as a supporting tool for the user.

Most of the existing work is still not associated with the recent significant progress in the machine learning field that suggests the use of deep features and neural networks. Deep learning methods have recently had high successes in medical imaging field [31], [32], but their use in clinical practices still remains limited. The reason behind this may be the scarcity of training data, since these approaches require enough training samples, which are not always available.

IV. FACE ANATOMY

To consider the face as a mirror of the health, it is important to understand what facial imaging is reflecting. A complex biological system lies below the superficial layer of the skin and each of its component can affect what can be seen. Eventually, the facial appearance depends on several factors. The most important is the morphology of the skull, defined by the concavities and convexities of the bones underlying the soft tissues. Thus, facial aesthetics are highly pre-determined by the facial skeleton features, such as the prominence of cheekbones or the protuberances in the inferior mandible [33].

Besides skull morphology, the appearance of the face is affected by features such as muscles to perform expressions, innervation allowing blood supply (venous drainage and branches of the carotid system), cutaneous sensory innervation [34] or fat compartments. Fig. 1 depicts the superficial fat compartments of the face, contributing to the face aspect. The activity of the facial muscles can reveal important information on the health condition of a subject. For example, while the partial loss of muscle activity is symptomatic of facial paralysis, involuntary movements can be characteristics of multiple conditions such as hemifacial spasm, Meige syndrome, dyskinesia, tics [35]. All the features related to the various systems and their interactions have to be taken into consideration in treatments involving facial procedures. While the injury of a facial nerve can affect its function and lead to clinical deficits, it can also result in local paralysis if a motor nerve is involved, to loss of sensation, decrease of taste, abnormalities in lacrimal activity or even salivary deficiency in cases of other nerves affected [36].

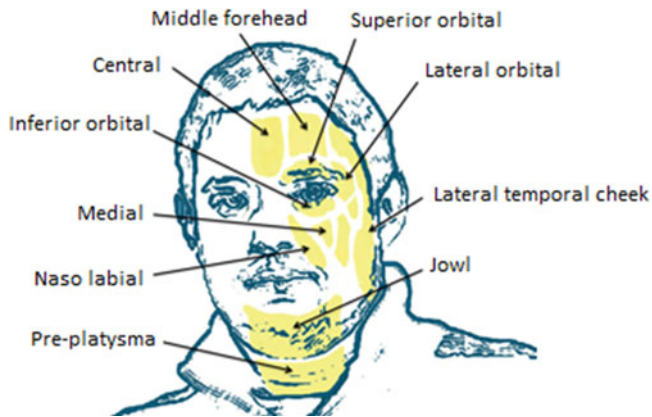


Fig. 1. The superficial fat compartments of the face.

Facial mapping, corresponding to the segmentation of the face into different regions of interest, has been extensively used in skin analysis based on facial location and the properties of the underlying tissues. From a point of view of computer vision, mapping the face allows to focus on areas that are highly relevant to specific conditions. Typically, the areas are defined from distinct facial anatomical landmarks such as the edges of the lips, the eyes, the nose and the contours of the face [37]–[39]. The areas defined between these landmarks have different information inherent of their locations. Eventually, in medical applications, the combination of data collected in each region of interest can provide indications on specific conditions.

V. AUTOMATIC DIAGNOSIS FROM FACIAL IMAGES

The assessment of facial symptoms can be crucial for the diagnostic of specific medical conditions. While a practitioner can study different facial features from careful observation, in some cases the challenging evaluation of subtle changes and their subjective assessment can alter the reliability of the diagnostic. Thus, computer vision was suggested as a solution to offer an automatic and objective assessment of facial features to help clinicians in their diagnostic [40]. This section addresses various applications of computer-based facial analysis: from basic monitoring of vital signs and assessment of pain, to the evaluation of specific conditions based on asymmetries, expressions, facial movements or facial heat distribution. For each condition, an overview of the different approaches is given with the most relevant outcomes reported.

A. Monitoring of Vascular Pulse

Plethysmography is the detection and measurement of volumes changes within the body. Its main application is the monitoring of the vital autonomic functions related to respiration rates and cardiac output (i.e., pulse). The study of cardio-vascular pulse waves traveling through the body and the monitoring of blood flow and its velocity, provide indications in the diagnostic of vascular disease [41], but also can help in the monitoring of conditions related to sudden infant death syndrome, sleep apnoea or pulmonary disease [42]. While different methods have been developed in the past to detect pulse [43], alternative

non-contact solutions based on photoplethysmography or thermal imaging, able to capture the pulsatile peripheral blood flow, have been promoted. Typically, the pulse waves from a dedicated light source are evaluated by assessing their variations in transmission and reflection on the surface of the skin. However, recent literature has shown that standard regular cameras can perform the pulse measurement in normal ambient light [44].

It has been suggested that the monitoring of physiological data can be used to assess the impact of physical exercise [45]. Furthermore, non-contact physiological monitoring can be applied in multiple domains such as telemedicine and homecare, since low-cost devices such as webcams, and smartphones can already perform the task [46]–[50]. Camera-based photoplethysmographs studies can be divided into two parts: the selection of regions of interest and their analysis. The first step of the process requires motion correction to reduce the impact of motion artifacts within the selected areas of interest. In this context, the positioning of the patient in a way that minimizes the face tracking is important.

The image analysis of the pulse often follows an approach based on color changes, typically using the information of the green channel of the RGB signal. Indeed, the green channel, highly correlated with variations in light, shows to be the most relevant to capture the pulse, while the red channel is useful to perform illumination correction [51]. The variations of the illumination-independent signal are analyzed along time, consolidating the fundamental signal frequency, corresponding to the pulse, and eliminating the possible noise [47], [48], [52]. Other color-based approaches have been performed using the HUE channel [53] or by a conversion to YCbCr (luma, blue chroma and red chroma) color space [54]. One of the main advantage of color-based analysis is the limited amount of facial pixels required to monitor the vascular pulse [42]. An alternative approach for measuring the pulse from facial video is to capture and track the subtle movements of the face, augmenting them using Eulerian video magnification [55]. Subsequent improvements of the system [56], [57] focused on the vertical movements of the head and the utilization of Fourier or Cosine transforms, and Principal Component Analysis (PCA). These methods obtain results with similar accuracy as color-based methods, but with improved robustness to illumination changes.

In most of these studies, the estimation of pulse is strongly correlated with the heart rate assessed from finger sensors or electrocardiograms, presenting 1–2% errors. However, while the acquisition process for monitoring the vascular pulse has been simplified, further challenges related to motion artifacts such as respiratory and head movements still require to be taken into consideration [51], [54]. It has been recently suggested [58] that using two regions of interest could be a solution to evaluate dynamic heart rate by detecting other physiological signs (e.g., eye blinking, yawning). Investigations are also still required to improve the robustness of the methods for different lighting conditions [59] and skin colors, while keeping the time span required to obtain the first confident evaluation of the heart rate as short as possible.

However, while the previous methods had latencies varying from tens of seconds [47], [48], [51] up to few minutes [50],

TABLE I
HOMOLOGY OF PAIN EXPRESSION ACROSS THE LIFESPAN

Muscular basis	Response
Corrugator	Brow lower ^{1,2,4,5,6} , brow bulge ³
Orbicularis oculi	Eye squeeze ^{1,3,4,5,6} , cheek raise ^{1,2,4,5} , lids tighten ^{1,2,5}
Levator	Nose wrinkle ^{1,4,5} , lip raiser ^{1,2,4,5,6} , eye closure ^{1,2} , nasolabial furrow ^{3,4}
Zygomatic	Lip corner pull ^{1,2,3,5}
Risorius	Horizontal mouth stretch ⁴
Pterygoid	Vertical mouth stretch ^{3,4,5}
Mentalis	Chin quiver ³
Nasalis	Flared nostril ⁴

¹Prkachin (adults) [61]. ²Prkachin & Solomon (adults) [62]. ³Grunau & Craig (neonates) [63]. ⁴Gilbert *et al.* (children) [64]. ⁵Kunz *et al.* (adults/elderly) [65]. ⁶Kunz *et al.* (young adults) [66].

[52] depending on the conditions of imaging acquisition, recent developments succeeded to reduce these times to few seconds [49] Finally, a study by Muender *et al.* [59] evaluated the feasibility of gathering heart rate from online videos as a step towards online physiological data collection. From their study, the potential applicability of heart rate assessment by online support requires not only a minimum network bandwidth (>16 mbps), but also good instructions to the participants to reach minimal offset error (<3 bpm).

B. Pain

Knowing the patient's pain is very relevant for practitioners and other health-care personnel to provide information on the state of the patient, and to suggest some preliminary medication such as painkillers. Extensive research related to automatic pain assessment has been performed. These studies have pinpointed the correlation of facial expressions with the activity of specific muscles, with regards to the age group population studied. A summary of the pain related facial movements adapted from Prkachin [60] can be seen in Table I. The Prkachin and Solomon FACS (Facial Action Coding System) pain scale is currently the only metric defining pain on a frame-by-frame basis [62]. The automatic recognition of pain expression can contribute to the reliability of pain measurements, improving the subjective assessment by practitioners. Pain assessment is at most relevance when the patient cannot express its suffering (ie. young age, mental condition, physical disability).

Some of the available databases rely on the use of facial videos from simulated pain expressions of actors, such as the Acted Facial Expression Database (STOIC) [67]. The database includes videos from 35 actors among which 15 sequences have been identified as expressions of pain. Another database without referential scale is the Infant Classification of Pain Expression (COPE) database, described in the work of Brahnam *et al.* [68]. This database, composed by 206 color images of 25 participants, has been used in multiple studies for the detection of pain from neonates' facial display [69]–[72]. The lack of baseline reference to grade the pain levels can be addressed by inducing a spontaneous painful reaction from external stimuli. The not publicly available Spontaneous Pain Expression Database

[73] which includes videos of expressions of 20 participants undergoing thermal heat stimulation at non-painful and painful intensities.

A more representative approach of induced pain has been described in the work of Lucey *et al.* [74], in the UNBC McMaster shoulder Pain Expression Archive database. This database contains more than 200 video sequences composed of 48,000 coded frames and the reported pain scores based on both self-reports and measurements from observers. This database brought a clinical baseline to the studies of pain by using a population suffering shoulder pain. Eventually, Ashraf *et al.* [75] and Lucey *et al.* [76] developed a method to detect pain using an active appearance model -based features extraction to cluster frames and to assign them a label to train a SVM classifier. Sikka *et al.* [77] improved the accuracy of pain classification from 68.31–80.99% up to 83.7% by using a multiple instance learning based on multiple segments representation. Such approach considers temporal information and issues related to label ambiguity. Finally, Kharghanian *et al.* [78] recently applied an unsupervised feature learning approach, raising the pain detection accuracy up to 87.2%.

An issue raised by databases without physiological information is that pain severity is assumed to be correlated solely with the intensity of the stimulus. This hypothesis does not have clear fundamentals, due to the bias induced by the personal subjectivity of pain. As an alternative robust baseline, the BioVid Heat Pain database [79] provides, in addition to facial expression videos, a synchronized collection of physiological data that measure a set of physical responses such as skin conductance level (SCL), electrocardiogram (ECG) and electroencephalogram (EEG). This database was generated to assess how combined facial features, head pose estimation and facial expression can relate an induced pain to physiological data. This publicly available database features videos of 90 participants grouped by age (18 to 65 years old).

The methodology used in facial pain analysis varies across studies. However, local descriptors have typically been used, as they showed statistically significant outcomes to discriminate pain in infant (90% accuracy) [72], or when related to estimated pain intensity (Pearson correlation 0.5 to 0.6) [80]. The compression of the data utilizing techniques such as PCA and the selection of robust classifiers like Support Vector Machines (SVM) [69]–[71], [75], [76] are also of importance. Other approaches such as tracking distances between face landmarks and evaluating the number of edge points in the nasal root as a detection of wrinkles have also shown their relevance [73]. Finally, Sikka *et al.* [81] developed an algorithm based on computer vision and machine learning to monitor the pain of children after appendectomy. Their model performed equivalently to the nurse in detecting pain, suggesting the relevance of developing tools to support the clinical personal.

The main challenge in studies related to pain is the establishment of a ground truth with reliable labels. A novel approach to collect data was suggested in the study of Hasan *et al.* [82], where they collected images and self-reported levels of pain by patients using a mobile app. While the use of mobile apps could ease the data collection process, special attention should

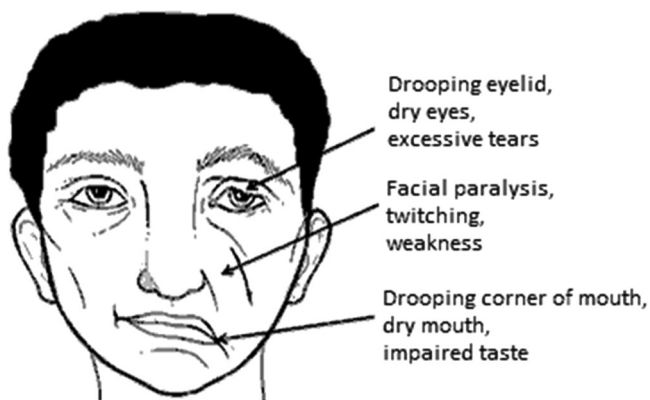


Fig. 2. An example of Bell's palsy.

be given to the reliability of data and ethical concerns which might raise from them. The generation of extensive and representative databases is of crucial importance to the realization of reliable and normalized pain studies.

C. Facial Paralysis

Facial paralysis commonly refers to the weakness of facial muscles, affecting their ability to perform movements and eventually, on a paralysis of the affected area. While facial paralysis can originate from supranuclear or nuclear lesions affecting the central part of the face, most of the facial nerve paralysis are caused by infranuclear lesions and affect solely one side of the face. Facial paralysis can have multiple causes such as Bell's palsy, infection, trauma, tumors, strokes and different syndromes such as Guillain-Barre or Moebius.

Computer-assisted diagnostic has been developed with a focus on the detection of bilateral asymmetries occurring in facial paralysis when subjects are typically requested to perform facial expressions (e.g., smiling). Image processing methods are able to measure the distances between anatomical landmarks and facial features and compare both sides of the face [83]–[89]. Furthermore, motion components can also be evaluated during the process to estimate facial muscular response from voluntary emotion [85], [90]–[93]. The accuracies of detection reported vary between 88.3% for smartphone camera acquisition (Linear Discriminant Analysis + SVM method) [88], up to 96.3% from conventional video cameras (Active Shape Models + LBP method) [89]. Finally, Hontanilla *et al.* [94] proposed a 3D system called FACIAL CLIMA to analyze facial motion. Their system, similar to stereo photogrammetry, uses three cameras to automatically assess the motions of anatomical landmarks on the face.

Bell's palsy is the most common cause of facial paralysis and has a poorly understood etiology. Fig. 2 depicts the possible symptoms of Bell's palsy, the most common cause of facial paralysis. Specifically, Bell's palsy is diagnosed clinically by a series of forced expressions to evaluate the weakness of specific muscles of the face. It has been suggested that a simple ruler can be enough to assess the severity of Bell's palsy by measuring bilateral anatomical asymmetries during specific muscles movements [95]. These asymmetries are related to nerve

damage, commonly assessed by electromyography which can also evaluate its severity [96]. Eventually, Barbosa *et al.* [97] used both iris segmentation and automatically detected key points location to assess asymmetries and diagnose palsy using a hybrid rule-based and machine learning classifier. As an alternative to standard video imaging, 3D measurements generated from space-coding method [98] as well as Kinect V2 [99], [100] have been suggested to detect facial asymmetries by retrieving 3D coordinates of facial landmarks.

Different studies tried to provide an objective solution to quantify the severity of the condition [84], [86], [89], [99], using the House-Brackmann facial nerve grading as a reference scale. However, this grading system has been criticized as it does not score accurately each facial function [101]. To address this issue, a tool called "Electronic Facial Paralysis Assessment" was described by Banks *et al.* [102], and was later validated against multiple grading scales (Spearman rho: 0.72 – 0.90) [103].

Methods developed for the diagnostic of Bell's palsy have also been tested in similar health conditions involving facial nerve dysfunction. In their studies, Linstrom *et al.* [104] and Wu *et al.* [105] used facial motion analysis to assess not only patients with Bell's palsy, but also patients with acoustic neuroma (intracranial tumor), glomus jugulare tumors, facial neuromas, parotid masses, temporal-bone fractures and essential blepharospasm (abnormal contraction of the eyelid).

Eventually, studies of bilateral asymmetries and synkinesis (involuntary muscular movements) demonstrated the ability of computer-assisted methods to accurately detect facial dysfunctions, reducing the impact of the subjective assessments performed clinically [105]. In addition, it was concluded that during a voluntary emotion, patients tend to exaggerate the muscular activity of the non-affected side to move the side affected by the condition. Methods based on analysis of the eyelid motion (blepharokymography) have also been developed to assess facial paralysis during blinking [106]. As an extended research on facial asymmetry using 3D-dynamics scans, Quan *et al.* [107] showed that captured facial dysfunction can also discriminate stroke patients, also suggested by Matuszewski *et al.* [108]. Similar study was performed using Kinect by Breedon *et al.* [109].

D. Neurologic Conditions and Neurodevelopmental Disorders

Neurological disorders refer to a group of diseases which affect the brain, spine and the nerves connecting them. Several of these conditions present symptoms suitable for computer vision methods. For example, the severity of neurological conditions such as Parkinson's disease can be assessed by tracking motions of the patients [110]. Similarly, video acquisition is clinically used with patients affected by epilepsy to track seizures [111], mainly to assess changes in both mouth and eye features [112], during an episode of abnormal neurological electric activity such as absence seizure [113].

Some birth defects can be discriminated from facial characteristics. For example, facial structural deformities induced by congenital diseases can be representative of specific conditions

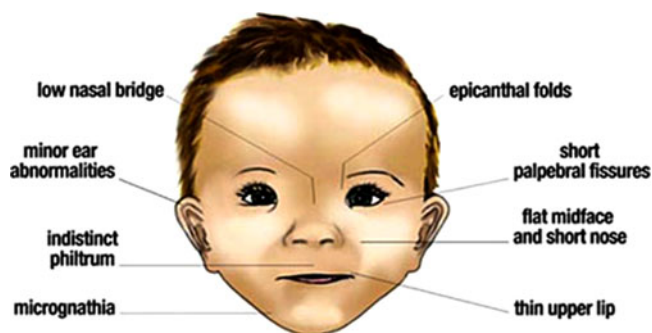


Fig. 3. Facial characteristics associated with fetal alcohol syndrome [132].

[114] and eventually used as classification criteria. In this context, computer-assisted tools have tried to classify people that present certain conditions, such as Down's syndrome [115], the Cornelia de Lange syndrome [116], or other syndromes [117] in an automatic way. Despite Down's syndrome having a defined set of facial features, individuals affected by the syndrome will generally present just seven or eight of them [118]. Moreover, the similitudes between siblings can make it challenging to distinguish people affected from non-affected relatives. In computer-assisted diagnosis, Down's syndrome assessment can be performed from a single image. A typical methodology consists in the detection of anatomical landmarks, then on the application of texture analysis using local descriptors, and finally on classifiers to discriminate affected subjects. Numerous works have focused on the automatic detection of subjects with Down syndrome [11], [115], [119]–[122]. The performance of the automatic discrimination methods reaches up to 97% accuracy from groups of infants. However, ongoing research is still being done, mostly to expand databases and increase the number of relevant features as well as classification methods [115].

The fetal alcohol syndrome is a birth defect related to high consumption of alcohol during pregnancy, which alters the normal development of the fetus and eventually leads to both physical and mental defects of the newborn. Fig. 3 shows the facial characteristics of individuals affected by fetal alcohol syndrome. Extended research has been performed to screen fetal alcohol syndrome from image analysis, based on specific facial phenotypes [123], [124]. Most of the research using computer vision to assess this condition has focused on both the measurements of the eyes and lips, as well as the smoothing of the philtrum. It has been shown that the assessment of the condition can be performed from simple facial images [125]. The obtained error rate is 14.3% of false negatives and no false positives [126].

To improve the assessment of the condition of fetal alcohol syndrome, 3D measurements taking into account the depth of the facial features have been performed by stereo photogrammetry [12], [127]–[130]. These studies lead to the development of a reliable device for anthropometric measurements for small infants. Mutsvangwa *et al.* [128] showed that these measurements can provide different accuracy for discriminating subjects affected by the symptoms depending on the age. Thus, the accuracy of the method for 5 years old subjects reaches

95.46%, while the rate decreased to 80.13% for 12 years old subjects. In addition to age grouping, Fang *et al.* [131] demonstrated that grouping patients based on their ethnic background provides better results. They used 3D facial laser scanning for patients and controls from two study sites (Finland and South Africa), with classification accuracies from 80% to over 90% by separating the cohorts.

The combination of anatomical landmarks and textural information allows to obtain a numeric representation of the face with numbers corresponding to well-defined features. It been suggested that multiple syndromic condition could be classified in clinical practice with such method [133], [134], despite overlapping features occurring in studies on facial dysmorphism [135]. However, one drawback is the manual intervention for landmark placement [136], [137].

E. Psychiatric Disorders

Psychiatric illnesses are disorders associated with abnormal behavioral and mental patterns compared to the social norm, causing suffering or disabilities in the daily life of the person affected. The diagnostic of mental conditions can be challenging due to unclear symptoms inducing a subjective assessment of the illness. For example, attention deficit hyperactivity disorder (ADHD) is the most common psychiatric disorder diagnosed among children. However, this syndrome shares multiple symptoms with other mental illnesses such as bipolar disorder [138]. The nature of ADHD remains poorly understood and its diagnostic still controversial [139], an issue quite common amongst different psychiatric conditions. As ADHD is characterized by symptoms such as hyperactivity, impulsivity, inattention, etc., Kinect has been suggested as a modality to assess behaviors of patients under specific tasks [140]. Eventually, Jaiswal *et al.* [141] created the database KOOMA, containing video and Kinect recordings of 55 subjects (controls, patients with ADHD/autism) listening, reading stories and answering questions. Using facial expression analysis and 3D analysis of behavior, they were able to reach a classification accuracy of 96% for controls vs condition groups (ADHD/autism), these disorders sharing some common symptoms between each other's.

Multiple studies on mental disorders revealed that the analysis of eye movement could greatly improve the diagnostics not only for ADHD [142], [143], [144], but also other psychiatric conditions [145], [146] such as schizophrenia [147]–[150], bipolarity [18], [150], autism [147], [151]–[153] or social phobia [19]. The basis of these studies is that people affected by these conditions will have specific types of ocular movement that could be symptomatic of illnesses or phobias [154]. Another approach by Benfatto *et al.* [155] was developed based on features extraction and SVM to classify children with dyslexia from control ones with 95.6% accuracy.

As the most common mental disorder, depression has been widely studied in order to quantify its severity in different groups of population [156]–[158]. It has been demonstrated that during a period of depression, a person affected is more likely to present facial expression disturbances, due to mood changes [159], [160]. The lack of objectivity in the measurement

techniques to evaluate depression encouraged the development of computer-assisted diagnostics. Typically, studies on automatic detection of depression are based on the analysis of head movement and facial dynamics from stimuli. Usually, the stimuli consist of specifically designed interviews. The facial responses are collected as a video and analyzed to determine special features associated with depression, with accuracies from 76.7% up to 79.0% [161], [162]. In addition to depression, a similar protocol has previously been applied in a study on schizophrenia by Wang *et al.* [163], demonstrating the inability of schizophrenic patients to express different emotions. Eventually, thermal imaging has been applied to assess facial thermal changes from induced emotion to classify moderate and high schizophrenia patients [164]. This study used MANOVA and SVM classifiers on features from the forehead, nose (representative area for stress analysis [165]) and right cheek, reaching an identification rate of 94.3%.

F. Mandibular Disorders

Temporomandibular disorder involves pain as well as a dysfunction of the muscles during mastication, inducing a restricted mandibular movement. The diagnosis is complex since the condition can have different etiologies. The use of thermal imaging has shown mixed accuracy depending on the aimed diagnostic. Extended research on temporomandibular disorder has been performed, mostly from the assessment of heat distribution obtained by thermal imaging [166]–[168]. Despite optimistic earlier studies suggesting the ability of thermal imaging to discriminate patients with an unspecific temporomandibular disorder with an accuracy in the range of 85–90% [169]–[172], recent studies focusing on diagnostics of specific conditions have shown mixed accuracies. For example, while skin temperature was proven to be associated with chronic myogenous temporomandibular disorder [173], thermal imaging failed to provide an accurate diagnostic of both this disorder [174], [175] and arthralgia [176]. However in these studies, the severity of the participants' conditions was not assessed before the tests, as demonstrated relevant in a following study [177].

It has been suggested that the studies of further forms of thermal analysis are required, not only to fill the lack of a standardized protocol for temperature measurements [174], but also to gain a deeper understanding of thermal patterns [176]. An improvement of the selection of the regions of interest is required, to assess a larger part of the muscles and to determine accurately which areas are related to specific mandibular disorders. Eventually, Haddad *et al.* [178] considered multiple regions of interest directly related to specific muscles. They reported that thermal imaging could be used as a supporting tool for clinical screening myogenous temporomandibular disorders but they also suggested that a stimulation (thermal, mechanical or chemical) could accentuate the results. This suggestion was further confirmed in another study involving thermal imaging and chewing test [179]. A profile thermal image is depicted in Fig. 4.

G. Other Conditions

The methods described in previous sections are suitable to be applied in other conditions as well. For example, the use of facial imaging has also been applied to evaluate facial abnormalities,

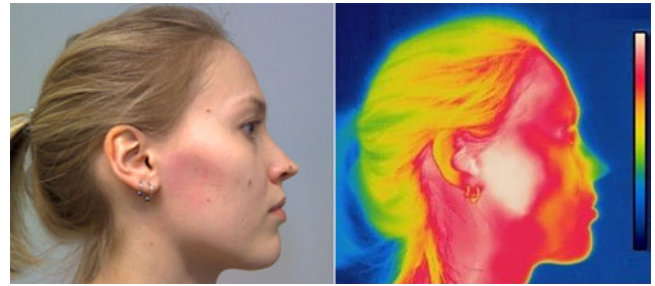


Fig. 4. Digital and thermal images of a subject with simulated inflammation (hot water exposure).

using facial features and classifiers to assess conditions such as acromegaly [180], [181] and Cushing's syndrome [181], [182] or craniofacial deformations associated with specific syndromes [13], [136].

In ophthalmology, video analysis and eye tracking have been suggested to assess conditions related to eye movement such as vertigo [183]. The monitoring of eyelids can be used in case of ptosis [184], as induced by ocular myasthenia gravis. Digital infrared thermal imaging has also been studied to assess orbital inflammation in Graves' ophthalmopathy [26], [185], or from non-specific conditions [186].

The objective assessment of the psychophysiological state of a subject can be made by measuring the arousal response or stress, where thermal imaging has shown to be a suitable technology [165], [187], [188]. Typically, these studies focus on evaluating the skin heat on regions of interest within the face, the periorbital and nasal areas showing to be the most discriminatory features.

Recent efforts have been made to establish the possible correlation between Traditional Chinese Medicine (TCM) -based face inspections with specific clinical conditions. In this context, the study of Hung *et al.* [189] used a TCM device to correlate face color with pulmonary function as a measure of the severity of bronchial asthma. Liu *et al.* [190] and Wang *et al.* [191] used facial chromaticity to identify patients with hepatitis. These studies suggest that establishing the relationship with chromaticity and medical conditions is of vital importance. The focus of these studies consists of two parts: the colorspace and the classifier used. There is a clear need to establish a publicly available database of pictures covering a wide range of different imaging conditions (e.g., lighting parameters) with a sufficient sample size.

VI. SUMMARY

The analysis of facial imaging can help to automatically detect some symptomatic facial features, in an objective manner. However, in most medical conditions, the final diagnosis of an illness is obtained from the combination of multiple symptoms. Table II provides an overall summary of the different facial symptoms accessible from automatic facial analysis as described in this survey. The possible conditions associated with these facial features are also reported, pointing out the risk of misdiagnosis. The published work related to each specific condition based on the facial feature is provided as reference. Furthermore,

TABLE II
OVERVIEW OF THE DIFFERENT DETECTABLE FACIAL SYMPTOMS AND THEIR ASSOCIATED MEDICAL CONDITIONS

Facial symptoms	Possible conditions	References	Facial symptoms	Possible conditions	References
facial morphology abnormalities/ characteristics	Down syndrome ¹	[11], [115], [119]–[122]	disturbances in facial expressions	depression ²	[161], [162]
	schizophrenia ⁴	[15]		ADHD ^{2,5}	[141]
	acromegaly ¹	[180], [181]	abnormal heat in orbital area	autism ^{2,5}	[141]
craniofacial deformations ^{1,4}	[13], [136]	schizophrenia ^{2,3}		[163], [164]	
fetal alcohol exposure ^{1,4}	[12], [123]–[131], [135], [136]	Graves' ophthalmopathy ³		[26], [185]	
	Cornelia de Lange syndrome ¹	[116], [133], [134]	asymmetry + synkinesis	nonspecific condition (Ophthalmology) ³	[186]
	Cushing's syndrome ¹	[181], [182]		facial nerve dysfunction ^{1,2}	
	other syndromes ^{1,4}	[117], [133], [134], [136], [137]			
facial asymmetry	facial paralysis ^{1,5}	[83]–[85], [97]–[100], [102]	abnormal eyelid movement	facial paralysis ⁵	[106]
	stroke patients ⁵	[107]–[109]		ptosis ²	[184]
abnormal eye movement	ADHD ²	[142]–[144]	abnormal iris area	facial paralysis ^{1,5}	[97], [98]
	dyslexia ²	[155]	abnormal muscular response	Bell's palsy and facial paralysis ^{2,4}	[85], [90]–[94]
	Parkinson ²	[144]		bronchial asthma ¹	[189]
	autism ²	[147], [151]–[153]	abnormal skin color	hepatitis ¹	[190], [191]
	schizophrenia ²	[147]–[150]	yellowish face color	torticollis ⁵	[16]
	bipolarity ²	[18], [150]	abnormal facial orientation	mandibular disorder ³	[169]–[179]
	social phobia ²	[19], [154]	heat in mandibular area	pain ²	[79]
	vertigo (ophthalmology) ²	[183]	abnormal head pose		
facial heat increase	acute respiratory syndromes ³	[23], [24], [18]	facial muscular contraction	pain ^{1,2,3}	[55], [68]–[82]

¹Standard digital imaging. ²Standard video imaging. ³Thermal imaging. ⁴Stereo photogrammetry imaging. ⁵Other imaging modalities.

TABLE III
OVERVIEW OF THE DIFFERENT CONDITIONS DETECTABLE, GROUPED BY IMAGING MODALITIES

Standard digital imaging	Standard video imaging	Thermal imaging	Stereo photogrammetry	Other imaging modalities
Neurodevelopmental and neurologic	Vascular pulse	Psychiatric	Neurodevelopmental and neurologic	Facial paralysis
	Psychiatric	Schizophrenia	Fetal alcohol exposure	Bell's palsy (blepharokymography), Facial paralysis (Microsoft Kinect™ / Cartesia™), Stroke related (3D Dynamic Scans / Microsoft Kinect™)
Down syndrome, Fetal alcohol exposure, Cornelia de Lange ...	ADHD, Autism, Depression, Schizophrenia, Bipolarity ...	Ophthalmology	Morphological abnormalities	Other conditions
Morphological abnormalities	Ophthalmology	Inflammation in Grave's and other conditions	Cranofacial deformations	Torticollis (Microsoft Kinect™)
Acromegaly, Cranofacial deformations, Cushing's syndrome	Vertigo, Ptosis	Dentistry	Facial paralysis	
Facial paralysis	Facial paralysis	Mandibular disorders		
Other conditions	Bell's palsy, Nerve dysfunction	Other conditions		
Hepatitis, Bronchial asthma	Other conditions	Arousal, Stress, Severe acute respiratory syndromes		
	Dyslexia, Absence seizure	Pain		
Pain	Pain			

multiple imaging modalities are available and can be used to detect specific symptoms requiring specific information from the face. Table III provides an overview of the conditions detectable from each imaging modality.

VII. DISCUSSION

Healthcare and wellness are common concerns for all populations. However, fulfilling the needs of the population in terms of healthcare services suggests a high cost for the society, derived partially from medical examination tests and practitioners' expenditures. To reduce these expenses, identifying diseases and

managing patients require some changes in the actual clinical protocols. Ideally, these changes would reduce the amount of patient examinations and decrease the time they spend in clinical facilities. While the time spent during the management of medical conditions can be rarely decreased (e.g., treatments), the resources spent to obtain an accurate diagnosis could be reduced with the help of automatic tools. Eventually, the diagnostics could be performed faster and in a non-invasive way avoiding any subjective bias.

The face is an interesting region of analysis, as it provides indications on multiple conditions and it is the body area the most accessible (unobtrusive). The present survey provided a list of

symptoms that could be assessed from facial imaging. Currently, these symptoms are clinically detected either directly by clinicians or by more expensive modalities. This review suggests that all the symptoms presented could be detected or at least assessed objectively using computer vision methods. As shown in Table III, in some cases the diagnostic of a medical condition can be provided by multiple imaging modalities, based either on the assessment of different symptoms of the disease or from alternative approaches specific to the imaging acquisition itself.

For each medical condition, the combination of multiple methods would reach a clinically acceptable accuracy for diagnostic, usable by the clinician as a support for its own decision [192]. The results from the computer vision analysis would not overrule the physician expertise, but be used for extra information as the patient can be affected by another condition sharing similar symptoms. This statement points out one common drawback of most of the studies presented here: the symptoms are assessed in controlled settings (patients affected by a condition vs. healthy control group) without considering interpersonal variability. Indeed, in real clinical environment, patients often present symptoms common to multiple diseases. To consider the variability, two separated models should be considered: a general one for patients with unknown condition giving some hints of possible diagnosis, and a person-specific one obtained from data acquired across time per single patient.

While most of the studies presented here aim to provide further assistance to clinicians in their diagnostic by quantifying specific features from images and videos, they can also be applied to detect a larger range of facial symptomatic characteristics subjectively. The combination of symptoms provides hints to the practitioner to formulate the final diagnostic. This standpoint further supports the need to perform multiple analysis to discriminate a specific condition out of a range of eventual diseases. For this purpose, information easily obtainable such as patient history or anthropometric data could be added in the analysis to help in the automatic diagnostic. Despite the clinical evidences of the studies described here, computer vision methods are still at the research stage in the medical field. One of the challenges of facial diagnostic is the impact of variable environmental conditions involved in long-range image capturing. While some successful applications (e.g., melanoma detection in dermoscopy field, pulse monitoring from light changes in the finger) have shown their applicability in close range image analysis, the variability of the results when capturing the image from long range has not yet been evaluated properly.

The main limitation to the development of computer vision methods for diagnosis from the face is the lack of publicly available data. While deep learning methods would be a good solution to improve the diagnostic tools based on facial features, they require an extensive amount of data to properly train the features extraction and classification models [31], [32]. Furthermore, the lack of transparency of the selected features could be an issue to be addressed for clinical applicability. In this review, the methods have been typically applied to a limited number of databases, reducing the relevancy of the studies. Despite the previously reported benefits of creating databases [193], [194], only a limited amount is available. A reason for this is ethical: the

access to personal medical data is under medical confidentiality agreements and involves ethical permits to perform specific research studies [195]. Thus, spreading the medical data for studies that were not mentioned in the original ethical permit is not allowed. Specifically, in facial analysis, this issue is at utmost importance, since the patient can be identified from its appearance, even when its anonymity is preserved.

To increase the relevance of the studies on facial analysis related to medical conditions, the improvement of ground truth data is required and for this purpose, some solutions should be considered. The development of collaborations between research groups from medical and computer science fields could highly improve the access to patient data. In addition, the integration of several acquisition modalities during patient examination could greatly increase the robustness of the decision systems (e.g., combination of image and clinical data). However, the multidisciplinary nature of the collaborations requires significant coordination efforts and joint facilities.

In perspective, alternative imaging modalities can be considered for computer vision methods for clinical purpose. The first one is mobile phones, the constant improvement of the hardware and the quality of their embedded cameras make them a perfect candidate for self-assessment. While multiple mobile applications related to health are available (e.g., Facial Dysmorphology Analysis technology Face2Gene [116], [117]), their use for clinical diagnostic remains limited despite being technically possible [88]. Furthermore, new hardware are being released (e.g., FLIR One), allowing to mount thermal camera on mobile phones, opening a new range of possibilities. Face images acquired using conventional cameras may indeed have inherent restrictions that hinder the inference of some specific details in the face. A promising approach for dealing with those limitations is using images acquired beyond the visible spectrum and/or using non-conventional imaging. With this aim, hyperspectral cameras are able to capture data into multiple bands of the electromagnetic spectrum both in the visible and invisible ranges. This imaging modality allows to identify the molecular composition of the scanned environment and the changes of its spectrum over time in the case of abnormalities due to medical conditions [196]. While hyperspectral imaging studies have mainly focused on getting tissue characterization from small-scale tissue samples [197], new methods for face analysis [198] and tongue cancer diagnosis [199] are emerging.

The combination of multiple imaging modalities and methods could lead to an increase of the accuracy of these predictive tools. However, the lack of standardization of the methodologies due to restricted access to clinical data to validate them has been restraining the emergence of novel solutions to assist the medical community.

VIII. CONCLUSION

This survey was carried out to assess the current state of evidence related to the implementation of computer vision systems for facial analysis applied to the diagnostic of medical conditions. In this review, a range of distant and non-invasive imaging solutions has been described, providing insights into

the suitability of each one of the techniques in the assessment of different types of symptoms related medical conditions.

The analysis of the work related to the traditional approaches of diagnosis from facial observations showed that the establishment of a correlation between face features and clinical data is of high importance. This relationship has been extracted from the review of more than 150 references, where the most relevant methodologies have been identified. The findings show that utilizing computer vision methods, over 30 conditions can be preliminary diagnosed from the automatic detection of some of their symptoms. This review reports clear evidences that the methods presented here could provide valuable tools for practitioners, eliminating subjective bias and reducing diagnostics time and costs. However, these systems still require further validations by clinical trials.

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