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Deducing health cues from biometric data

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ABSTRACT

Medical diagnosis involves the expert opinion of trained health care professionals based on causal inference from medical data. While medical data are typically collected using specialized medical-grade sensors, similar data characteristics useful for medical diagnosis are sometimes present in biometric data (e.g., face images, ocular images, and speech signals). In this paper, we explore the biometrics and medical literature to study the following questions. 1) What kind of health cues are embedded in the commonly utilized forms of audio-visual biometric data? 2) How can these health cues be gleaned from the biometric data, and what kind of diseases can it help diagnose? 3) What are some of the implications of using biometric data for medical diagnosis?

1. Introduction

Biometrics refers to the science of recognizing individuals from their physical and behavioral attributes, referred to as biometric modalities (Jain et al., 2011). While biometric data is primarily collected to verify or establish a person's identity, it often encodes extra information beyond an individual's identity (Dantcheva et al., 2015; Ross et al., 2019). For example, a person's face image can also reveal demographical (such as age and gender) (Zhang et al., 2004) and anatomical (such as craniofacial and muscular characteristics) (Sgroi et al., 2015) information. Additionally, the physical and behavioral attributes of an individual that are embedded in the biometric data can implicitly encode associated health information (Diaz, 2021). For example, the anatomical details of a person's face image can help detect underlying disorders such as Down syndrome. Therefore, some health cues can be potentially extracted from the biometric data that may aid in medical diagnosis.

Biological signals, such as electrical brain activity, are primarily collected to assess the health of an individual and often employ sophisticated and expensive data collection instruments, such as an electroencephalogram (EEG) machine. In contrast, biometric data such as face images are primarily collected to determine or verify the identity of an individual and can be captured using relatively inexpensive consumer devices, such as a smartphone camera. The number of acceptable *biometric* modalities in use are much fewer than the wide variety of plausible *biological* signals. This is because of practical constraints relevant to biometrics (Grother et al., 2013; Jain et al., 2011) such as uniqueness, permanence, non-invasiveness, etc. For example, electrocardiogram (ECG) data can also be used to perform biometric recognition (Odinaka et al., 2012). However, the relatively invasive ECG data collection procedure limits its acceptability as a biometric modality. At the same time, the availability of biometric data collected using affordable consumer devices, such as smartphones and smartwatches, paired with sophisticated machine learning tools, has prompted researchers to study the automated detection of health cues from biometric data. For example, smartphone applications have been developed to detect unhealthy gait patterns from a smartphone's accelerometer data (Juen et al., 2014). Therefore, the prospect of extracting health cues from available biometric data using automated data-driven approaches has witnessed an interest, although there are some legitimate privacy concerns surrounding the use of such data for unintended purposes. In this paper, we examine biometric data from the perspective of its utility in medical diagnosis. Specifically, we answer the following questions: (1) What kind of health cues are embedded in the biometric data, (2) How can these health cues be reliably gleaned from the biometric data, and what kind of diseases can it help diagnose? (3) What are some of the implications of using biometric data for medical diagnosis?

In the upcoming sections, we review the state-of-the-art in deducing health cues from four different biometric modalities (Fig. 1). We investigate (i) face (Fig. 2) in Section 2, (ii) ocular (Fig. 4) in Section 3, (iii) voice (Fig. 8) in Section 4, and (iv) gait (Fig. 9) in Section 5. See Table 1 for an overview of the health disorders investigated, datasets used and findings reported in the existing literature for the four principal biometric modalities considered in this work. Furthermore, we analyze the challenges associated with extracting health cues from biometric data and its associated privacy-implications in Section 6. Finally, we draw the conclusions of this survey in Section 7.

2. Face modality

Face recognition requires analysis of discriminative features extracted from face images. These facial features pertain to anatomical

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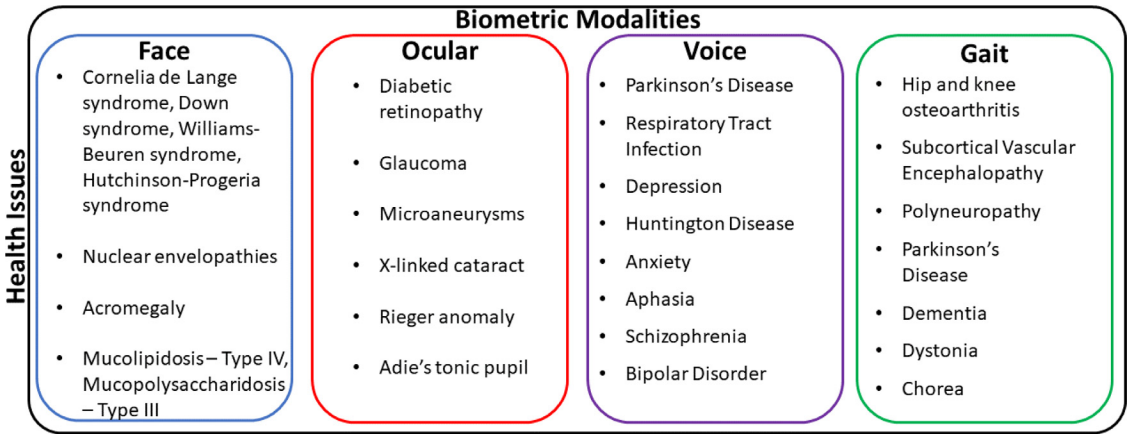


Fig. 1. A brief overview of different health ailments detectable from various biometric modalities.

Table 1
Examples of health disorders investigated and the evaluations conducted with respect to the four modalities considered in this work. NA means not available.

Modality	Health disorder (Physiological/Psychological/Genetic)	Dataset specifications		Performance
		Name and availability	# of Subjects	
Face	*Physiological*: BMI, blood pressure, height prediction, drug abuse *Psychological*: Depression, apathy *Genetic*: Down's, Cornelia de Lange, Acromegaly, Noonan syndromes	Wen and Guo (2013): MORPH-II dataset (Public) Dantcheva et al. (2018): VIP_attribute (Public) Giannakakis et al. (2020): Stress dataset-SRD'15 (Proprietary) Happy et al. (2020): Experimental dataset (Proprietary) Gurovich et al. (2019): Clinical test set (Proprietary)	Wen and Guo (2013): 9181 Dantcheva et al. (2018): 1026 Giannakakis et al. (2020): 24 Happy et al. (2020): 45 Gurovich et al. (2019): NA	Wen and Guo (2013): BMI prediction MAE = 3.0 ± 1.0 Dantcheva et al. (2018): Height estimation MAE = 0.07 ± 0.005 Giannakakis et al. (2020): Stress detection accuracy = 74.6% Happy et al. (2020): Apathy classification accuracy = 80.0% Gurovich et al. (2019): Top-10% Syndrome classification accuracy = 91%
Ocular	*Physiological*: Glaucoma, diabetic retinopathy, microaneurysms (MAs) *Genetic*: X-linked cataract, pigment dispersion syndrome	Wang et al. (2017): Moorfields eye hospital dataset (Proprietary) Wang et al. (2019): Diabetic retinopathy challenge dataset from Kaggle (Public) Niwas et al. (2015): Clinical dataset (Proprietary) Czepita (2020): Clinical dataset (Proprietary)	Wang et al. (2017): NA Wang et al. (2019): NA Niwas et al. (2015): NA Czepita (2020): 4	Wang et al. (2017): MA detection sensitivity = 96.3% Specificity = 88.4% Wang et al. (2019): Lesion detection AUC = 0.99 Niwas et al. (2015): Glaucoma detection accuracy = 86.6% Czepita (2020): Pigment dispersion average aperture = 1321.53 (ADU) ± 501.08 SD
Speech	*Physiological*: COVID-19, Parkinson's disease *Psychological*: Depression	Han et al. (2020): Experimental dataset (Proprietary) Huang et al. (2020): SH2-FS (Public) Huang et al. (2020): DAIC-WOZ (Public) Pompili et al. (2020): Experimental dataset (Proprietary)	Han et al. (2020): 52 Huang et al. (2020): 566 Huang et al. (2020): 142 Pompili et al. (2020): 180	Han et al. (2020): COVID 19 severity classification accuracy = 69% Huang et al. (2020): Unweighted Averaged Recall (UAR) for depression detection = 0.73 Huang et al. (2020): Unweighted Averaged Recall (UAR) for depression detection = 0.91 Pompili et al. (2020): Mean Parkinson's disease detection accuracy = 92.5%
Gait	*Physiological*: Effect of age on musculoskeletal health	Majumder et al. (2018): Experimental dataset (Proprietary)	Majumder et al. (2018): 74	Majumder et al. (2018): Age classification accuracy = 88%

and structural details present in an individual's face. Facial dysmorphism due to genetic disorders, such as Down's syndrome, can affect the facial phenotypes such as the shape and structure of the face, which can be leveraged by machine learning-based algorithms for diagnosis (Burçin and Vasif, 2011). Therefore, in this section, we explore the existing literature that employs face images for medical diagnosis. In Loos et al. (2003), the authors used frontal photographs of patients and applied the bunch graph matching algorithm (Wiskott et al., 1997) for detecting genetic disorders (Cornelia de Lange, Williams-Beuren, fragile X, mucopolysaccharidosis — Type III and Prader–Willi syndrome). Evaluations indicated that the 'syndrome classifier' achieved 76% accuracy compared to 62% classification accuracy achieved by the six geneticists used for comparison. This work motivated exploring the genetic variation of the facial 'gestalt' for diagnosis. Similar work was conducted (Boehringer et al., 2006), with additional syndromes and an intermediate dimensionality reduction step. In Hammond et al. (2005), the authors computed dense surface models using twenty-one 3-D landmark points manually annotated on three-dimensional face images for detecting Williams, Smith-Magenis, 22q11 deletion, and Noonan syndromes. A dense surface model comprised a set of modes obtained after applying principal component analysis on the residuals between the mean and the training surfaces (faces pertaining to each syndrome) which was then subjected to linear discriminant analysis, support vector machine, and closest mean for classification. Another

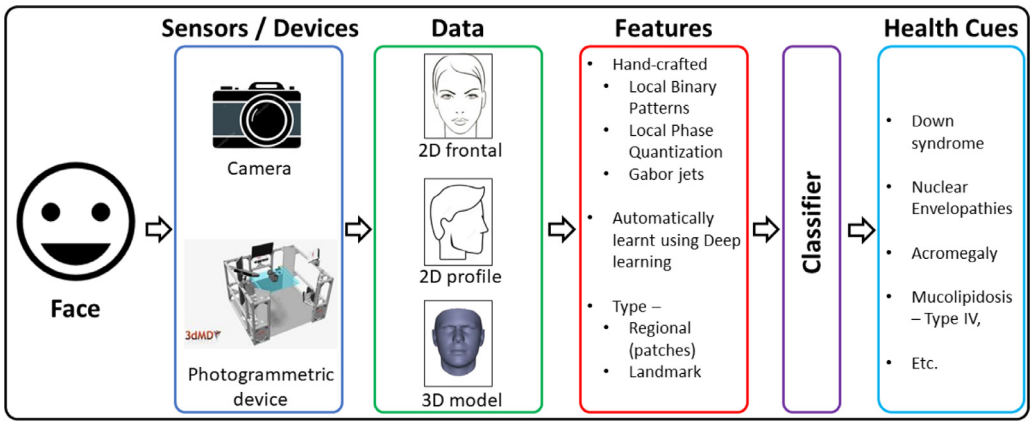


Fig. 2. Deducing health cues from the face modality.

work applied 3D facial morphometric phenotyping on 3D photgrammetric images for automated syndrome classification (Hallgrímsson et al., 2020).

Acromegaly is a rare disorder resulting due to GH (growth hormone) excess, primarily due to pituitary adenoma which can cause multimorbidity and increased mortality. Authors in Schneider et al. (2011) used Gabor jets for texture analysis and a geometry-based approach for detecting acromegaly (mild, moderate, and severe) using frontal and side photographs of patients with an overall performance of 81.9% compared to 72.1% achieved by experts.

In Cao et al. (2012), the authors estimated weight and gender by investigating head and other body measurements using a copula model. The weight estimation can help with body mass index (BMI) prediction that can be used to examine cardiovascular health and diagnose disorders such as hypertension. The authors in Wen and Guo (2013) developed a computational approach to automatically predict BMI using a combination of machine learning and statistical approaches. They evaluated the proposed method on 14,500 face images, and demonstrated statistically significant correlation scores between facial features and BMI. Geometric morphometric methodology (GMM)-based approach analyzed the variations in the face shape for detecting physiological health cues from face images (Stephen et al., 2017). The face images were automatically annotated using Psychomorph software, followed by GMM modeling. Hierarchical linear regression was applied to produce models to predict percentage body fat, BMI, and blood pressure factor from facial shape components. Height, weight and BMI were predicted from face images using a regression model applied to a deep learning-based neural network (Dantcheva et al., 2018). In Jiang et al. (2019), the authors investigated the effect of geometric-based and deep learning-based facial representations (features) on the performance of visual BMI estimation, redundancy in feature representations, and sensitivity to variations in head pose.

Although machine learning-based facial analysis for diagnostic applications was already in use, it attained significant strides with the advent of deep learning. DeepGestalt (Gurovich et al., 2019), the technology behind Face2Gene (Gurovich, 2020), was hailed as the pioneer of next-generation phenotyping (NGP) that leveraged deep learning for diagnosis from facial images. The methodology involved face detection using a cascaded deep convolutional neural network (DCNN), followed by facial landmark detection. Then the face was cropped into multiple regions, each region occupying a fixed size, and each region was processed by a separate deep neural network. Each region-based DCNN output a vector of probability values, where each value indicated the probability of the individual to have a particular syndrome. Finally, the region-based results were aggregated to obtain a ranked list of genetic syndromes. See Fig. 3. Evaluations indicated that the DeepGestalt model achieved 91% top-10 accuracy, *i.e.,* it was able to predict the top 10 syndromes correctly. The results validated its utility as a reference tool for clinicians. Face2Gene (FDNA Inc.) uses the DeepGestalt to determine and further correlate the phenotype to its corresponding genotype for several hundreds of disorders (Gurovich, 2020). It provides a community-based platform that allows doctors to upload face images of patients for diagnosis, which can help drive the training process. Therefore, it provides an efficient and effective AI-driven solution that aids the medical and the research community in parallel.

DeepGestalt has been used for identifying Mucolipidosis Type-IV (ML-IV), a rare autosomal-recessive disease (Pode-Shakked et al., 2020), for detecting nuclear envelopathies which are rare disorders caused by gene mutation resulting in a variety of phenotypes mimicking the effect of ageing (Marbach et al., 2019), for detecting Cornelia de Lange syndrome (Latorre-Pellicer et al., 2020), and for detecting Noonan syndrome (Kim et al., 2019). Phenotypic information cannot be used in its raw form for diagnostic evaluation by exome sequencing. Prioritization of exome data by image analysis (PEDIA) (Hsieh et al., 2019) used the scores generated by the DeepGestalt to quantify the variant interpretation.

Psychological disorders, such as depression detection from face images have been extensively studied; the readers are referred to Pampouchidou et al. (2019) for a comprehensive overview of the literature. The authors in Ee et al. (2011) used eigenface and Fisherface features to predict whether an adolescent is likely to develop clinical depression within the next 1–2 years. In Wen et al. (2015), the authors performed local phase quantization from three orthogonal planes (LPQ-TOP) for depression classification from facial images. Deducing mental health cues from face images acquired while logging into smartphones have been explored (Wang et al., 2015). In Giannakakis et al. (2020), the authors performed automated stress detection from face images by estimating the intensity of facial action unit using geometrical and appearance-based features followed by a support vector regressor. Apathy classification using a multi-task learning paradigm which incorporated both emotion and facial movements from video sequences was conducted (Happy et al., 2020).

Thermal face images can be used for detecting fever in individuals which can be crucial for screening patients affected with acute infectious diseases, like coronavirus disease (COVID 19) (Zhou et al., 2020). Thermal face images were processed for accurate eye localization using template matching and other methods for measuring the inner canthus (eye corner) temperature as an indicator for overall body temperature (Budzan and Wyżgolik, 2013).

In Yadav et al. (2016), the authors studied the performance of commercial face recognition algorithms on subjects addicted to methamphetamine, cocaine, heroin and crack, and observed a sharp degradation in the recognition accuracy due to severe changes in the faces. The authors proposed a dictionary learning-based approach for classifying drug abuse face images with a higher success rate compared to other

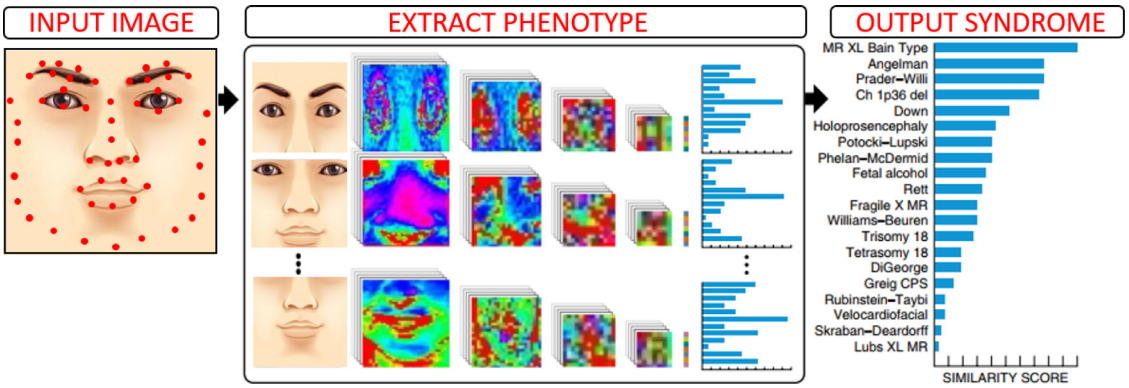


Fig. 3. Illustration of the pipeline of the processing performed by the DeepGestalt. Image partially reproduced from Gurovich et al. (2019). The patient image in the original paper (Gurovich et al., 2019) has been substituted with a graphic for privacy reasons.

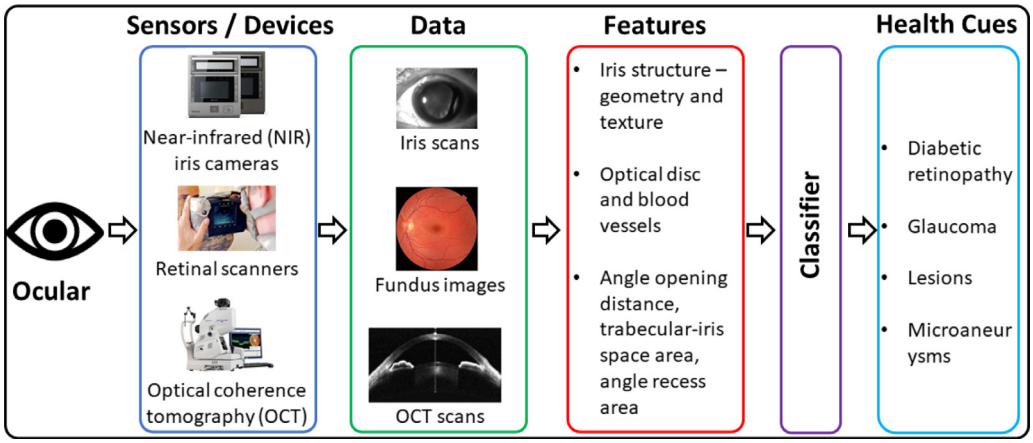
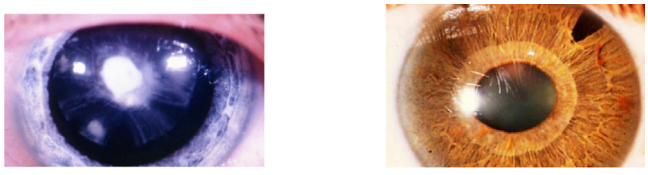


Fig. 4. Deducing health cues from the ocular modality.

approaches. In Harastani et al. (2020), the authors investigated the effect of meth abuse on facial asymmetry. They validated that there is a natural tendency of an increase in facial asymmetry with age. However, the asymmetry is significantly increased in the case of drug abusers. This is because meth consumption accelerates the biological aging process which in turn causes severe distortion of faces as age progresses. As a result, the facial asymmetry in drug abusers is up to 3 to 5 times higher than in ordinary people. The authors claimed that the exaggerated facial asymmetry with age that can adversely impact biometric recognition could be leveraged for detecting drug addicts as their faces show severe distortions due to illicit drug abuse.



(a) (b)

Fig. 5. Examples of abnormal irides due to (a) genetic disorder — X-linked cataract, and (b) developmental disorder — Rieger anomaly.
Source: Images are taken from Morrison (2010).

3. Ocular modality

Examination of ocular images can help in diagnosing chromosomal or developmental disorders through abnormalities observed in the iris, sclera, and cornea (Morrison, 2010). See Fig. 5. Typically, iris recognition requires near-infrared illumination for data acquisition, but it can also be achieved using ocular images captured in the visible spectrum for individuals with light-colored irides (Proenca et al., 2010; Jillela and Ross, 2015; Boyce et al., 2006; De Marsico et al., 2015). As a result, the investigation of ocular images in the visible spectrum can be leveraged to indicate genetic disorders (Morrison, 2010).

Some work investigated anatomical anomalies (see Fig. 6) in iris images captured in the near-infrared spectrum; these anomalies can adversely impact iris recognition (Aslam et al., 2009; Trokielewicz et al., 2015). The authors in Trokielewicz et al. (2015) observed a significant degradation in the performance of iris recognition (in terms of genuine scores) when comparing healthy irides with irides suffering from disorders that can produce visually discernible changes to the iris.

Diabetic retinopathy (DR) was detected from fundus (includes retina, optical disc, fovea, etc.) images by locating microaneurysms (MA) which are primary indicators of DR (Wang et al., 2017). MAs appear as reddish dots on the retina. See Fig. 7. The authors extracted the candidate regions by filtering out dark regions corresponding to vessels, lesions, and noise compared to MAs, which typically have lower intensity. Then they performed singular spectrum analysis (SSA) on cross-section profiles of each of the candidate objects. SSA generated a discriminative set of features devoid of spurious vessel crossings; these features served as input to classifiers for MA detection. The sensitivity of the best classifier (proportion of correctly detected MAs out of a total number of MAs) was 96.3% and specificity (proportion of correctly detected non-MAs out of a total number of non-MAs) was 88.4%. Retinal lesions from fundus images were detected using a weak supervision technique in Wang et al. (2019), which jointly modeled the lesions and the background noise as a stochastic multimodal distribution of a mixture of Gaussians. Weak supervision provided by the normal images

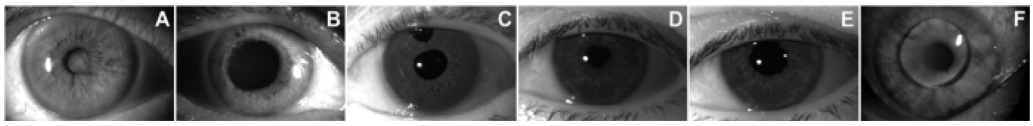


Fig. 6. Ocular pathologies investigated in Trokielewicz et al. (2015). A: cataract, B: acute glaucoma, C: iridectomy, D: synechiae before lens replacement, E: synechiae after lens replacement, and F: silica oil in the anterior chamber of the eye.
Source: Images are taken from Trokielewicz et al. (2015).

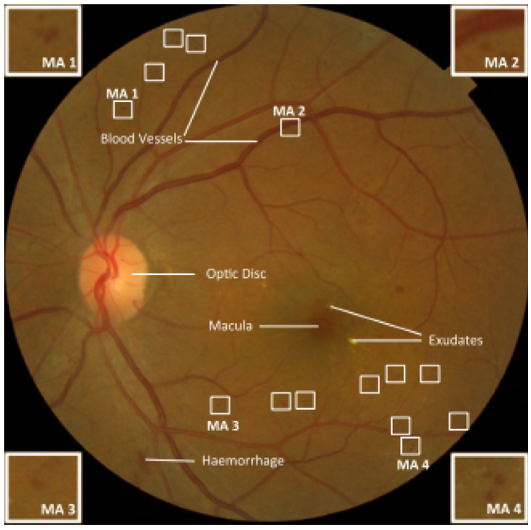


Fig. 7. Illustration of pathological indicators of diabetic retinopathy such as microaneurysms (MA) (indicated by the white bounding boxes), haemorrhage and exudates.
Source: Image is taken from Wang et al. (2017).

helped eliminate the background noise, thereby correctly identifying the lesions in abnormal images.

Work on detecting glaucoma (angle-closure glaucoma) by assessing the anterior chamber angle using optical coherence tomography (OCT) was conducted in Niwas et al. (2015). Detection of Adie's tonic pupil and pigment dispersion syndrome using near-infrared transillumination with customized aperture photometry was conducted in Czepita (2020). However, these analyses do not use ocular images used in conventional iris and retinal recognition (Veen, 2020).

OCT has gained prominence in detecting neurogenerative disorders from ocular images. OCT detects structural changes in the retina by providing 2-D cross-sectional image and 3-D volumetric representation of the retina, that can be used for assessing ophthalmologic and neurologic diseases such as glaucoma and sclerosis. Additionally, OCT studies have been used to detect retinal degradation such as thinning of the retinal nerve fiber layer (RNFL) and other structural changes observed in patients with Alzheimer's disease and mild cognitive impairment (Snyder et al., 2021). Optical retinal imaging can detect abnormal protein aggregation, such as β-amyloid plaques, which can allude to the presence of diseases such as Alzheimer's, Parkinson's, Huntington's, etc. (Colligris et al., 2018). OCT exhibits tremendous promise in neuro-ophthalmology due to the development of advanced techniques such as spectral-domain OCT, swept-source OCT, enhanced depth imaging OCT and recently, OCT angiography, capable of assessing retinal and choroidal vascular network and blood flow. This can be used for detecting diseases such as optic disc drusen (de Carvalho and Maloca, 2020).

4. Voice modality

As a mode of communication, the human voice carries vast amounts of information apart from the speech content, such as the identity, sex, and even the health condition of the speaker. Recently, the human voice has been gaining traction as a biological signal for various physical and psychological diseases and disorders (Latif et al., 2020). One of the largest benefits of using the human voice as a biological signal is its ease of acquisition. Voice acquisition does not require any specialized medical-grade hardware and a relatively low-cost consumer-grade microphone is adequate for this purpose. The currently ongoing COVID-19 pandemic has seen the emergence of several human voice-based affordable and reliable diagnostic tools for ensuring high quality and timely healthcare. For example, Albes et al. (2020) developed a computationally efficient and affordable Internet of Things (IoT)-based remote health monitoring device for detecting Upper Respiratory Tract Infection (Cold and Flu), an important marker for the COVID-19 pandemic. Another such work (Han et al., 2020) developed an intelligent speech analysis tool for monitoring the severity of illness in COVID-19 diagnosed patients. Specifically, the authors used the extended Geneva Minimalistic Acoustic Parameter Set (eGeMAPS) to extract speech features. They paired it with a Support Vector Machine classifier to estimate the level of severity of the corresponding patient.

Intelligible and coherent speech production in humans is accomplished by many physiological and psychological processes working together. Therefore, any loss of speech intelligibility or coherency can potentially indicate the presence of an underlying physiological or psychological ailment (Quintas et al., 2020). Therefore, early and accurate detection of such speech anomalies is critical for providing timely healthcare to the affected individuals. To this end, significant research is being done to develop affordable and accurate diagnostic and therapeutic tools by leveraging the recent advancements in speech processing and machine learning techniques. For example, the authors in Abraham et al. (2020) developed a tool for the automatic assessment of articulatory errors in the speech of children with hearing impairment (CHI). The authors assessed the severity of the articulatory errors from the burst duration and spectral moment of plosives in the speech of CHI. Speech-Language Pathologists can use this tool to formulate an appropriate speech therapy plan based on the severity of the errors. In another similar work, the authors develop a speech assessment tool to assist clinicians in diagnosing and treating motor speech disorders, such as apraxia of speech (AoS) and dysarthria. The authors in Kodrasi et al. (2020) proposed multiple sets of handcrafted speech features to train multiple Support Vector Machine (SVM) classifiers and fused them at the decision-level to differentiate between AoS and dysarthria from speech audio.

In the upcoming sub-sections, we will discuss some healthcare issues where the recent advancements in speech processing and machine learning techniques have been successfully used to develop fast, accurate, and affordable diagnostic tools.

4.1. Depression detection from speech

Major Depressive Disorder (MDD), also known as clinical depression, is a mental health disorder that causes a persistent feeling of sadness and general disinterest and can interfere with a person's daily functioning (Belmaker and Agam, 2008). MDD often causes changes in speech production and articulation due to psychomotor slowing (Seneviratne et al., 2020). These speech articulation changes can be detected from free speech audio to diagnose MDD in the speaker and form the basis of various research efforts in this direction. For

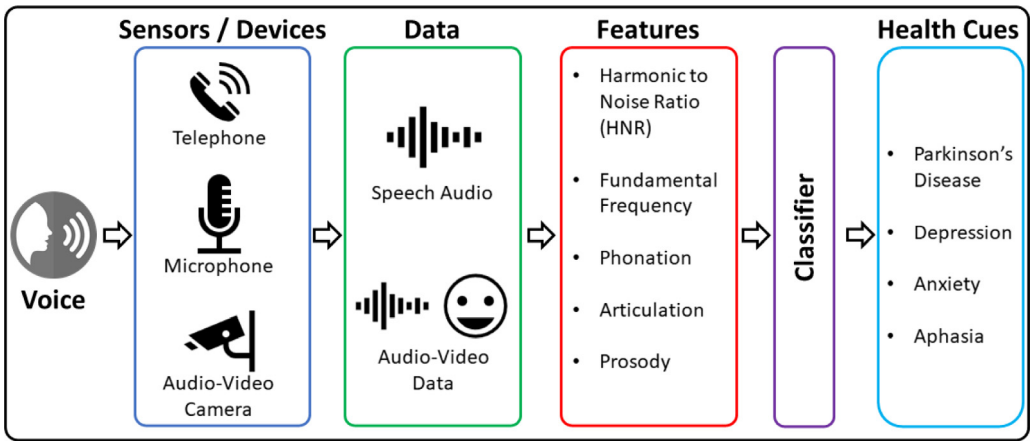


Fig. 8. Deducing health cues from the voice modality.

example, authors in Seneviratne et al. (2020) use a Support Vector Machine (SVM) classifier to detect MDD from the articulatory speech features from free speech audio. Specifically, they use speech-inverted vocal tract variables (TVs) and Mel Frequency Cepstral Coefficients (MFCC) to characterize the articulatory speech features. However, this approach uses speech data collected in a controlled experimental environment; thus, no comments can be made on its generalizability to uncontrolled everyday speech environments. Towards this end, authors in Huang et al. (2020) proposed multiple domain adaptation strategies to adapt deep learning-based pre-trained depression detection models to improve depression detection performance in uncontrolled speech environments. In another similar work (Alghowinem et al., 2013b), the authors combined multiple classifiers (at score level), including Gaussian Mixture Models (GMM), Support Vector Machines (SVM), Multi-Layer Perceptron (MLP), and Hierarchical Fuzzy Signature (HFS) classifier for improving depression detection from spontaneous speech data. The authors also showed that loudness, Root Mean Square (RMS) energy, and intensity were the best-suited speech features for detecting depression in their experiments. Furthermore, the authors in Alghowinem et al. (2013a) showed improvement in SVM-based clinical depression detection from spontaneous speech compared to read speech. This is due to the larger acoustic variability in spontaneous speech due to its unrestricted nature allows for a better representation of depression-related speech characteristics. While MDD is known to affect articulation in the speech production process, it also affects the patient's speaking style due to its effect on their emotional state. Therefore, prosodic speech features related to the speaker's emotional state can indicate depression in their voice. One such work (Moore et al., 2003) developed a method for capturing emotional variations manifested in speech prosody and captured by pitch, energy, and speaking rate feature statistics of the human voice for detecting MDD.

MDD detection from speech audio using machine learning techniques is currently on the rise. However, it is also essential to assess the severity level of the depression in the patients as the healthcare options can be customized based on the level of severity. Towards this end, the authors in Yamamoto et al. (2020) demonstrated the association between timing-related speech features and depression severity. Specifically, the authors found that depressed patients showed a slower speech rate, longer pause time, and longer response time than healthy patients. Therefore, timing-related speech features are particularly suitable for detecting depression severity. Another similar work (Zhao et al., 2020) combined self-attention network (SAN) and deep convolutional neural networks (DCNNs) to extract depression-related speech characteristics for assessing depression severity. In this work, the SANs were used due to their superior ability to model timing-related speech features, while the DCNNs were used to capture the spatial information from 3D log-Mel spectrograms. Combining the complementary speech features extracted by the SAN and DCNN models enables the hybrid network architecture to reliably perform depression severity detection.

4.2. Parkinson's disease detection from speech

Parkinson's disease (PD) is a neurodegenerative disorder characterized by shaking, stiffness, and difficulty with balance and coordination while walking (Dauer and Przedborski, 2003). Typically by the time PD is detected, the disease has already caused significant deterioration to the patient's condition, thus increasing the healthcare challenges for both the patient and the care providers. Therefore, it is essential to develop new diagnostic techniques that can allow for early diagnosis and, consequently, timely treatment of the disease. It has been noted that PD affects human speech very early in its progression. Patients with PD exhibit disabilities and disturbances in speech production such as monotonic speech, weakness in the vocal musculature, reduced loudness, and breathy voice, thus affecting their speech intelligibility (Hosseini-Kivanani et al., 2019). Furthermore, these speech impediments worsen with the progression of the disease (Kim et al., 2015). Automatic speech processing techniques can, therefore, be used to aid in the early diagnosis and monitoring of PD (Pulido et al., 2020).

One of the recent works in this direction (Frid et al., 2014) developed an automatic Parkinson disease detection method directly from natural speech without human experts' assistance. The authors used the pitch, short-time energy, zero-crossing rate, and MFCC features of the speech signal to characterize the PD-affected speech characteristics. A Support Vector Machine classifier was used to detect PD from the input speech features. Another similar work (Kadiri et al., 2020) proposed replacing the MFCC features commonly used in PD detection frameworks with single frequency filtering (SFF) based cepstral features, called single-frequency filtering cepstral coefficients (SFFCCs), to improve their PD detection performance. The SFF-based features are shown to provide higher spectral and temporal resolution for deriving speech features, thus better capturing the PD-related speech characteristics. The authors used the SFFCC to derive an iVector representation of the input speech audio. The iVector was then classified using an SVM model to detect PD. Another work (Gope and Ghosh, 2020) developed a data-driven approach to learn speech representation directly from raw audio to characterize Parkinson's disease's effect on speech. The authors used a 1-Dimensional Convolutional Neural Network (1D-CNN) followed by a Bidirectional Long Short-Term Memory (BLSTM) to detect PD directly from raw speech audio, in contrast to the hand-crafted features used in Frid et al. (2014).

Parkinson's disease's progression is often marked by alternating periods of motor symptoms called ON and OFF states. The ON state is associated with the period in which the medications can mitigate

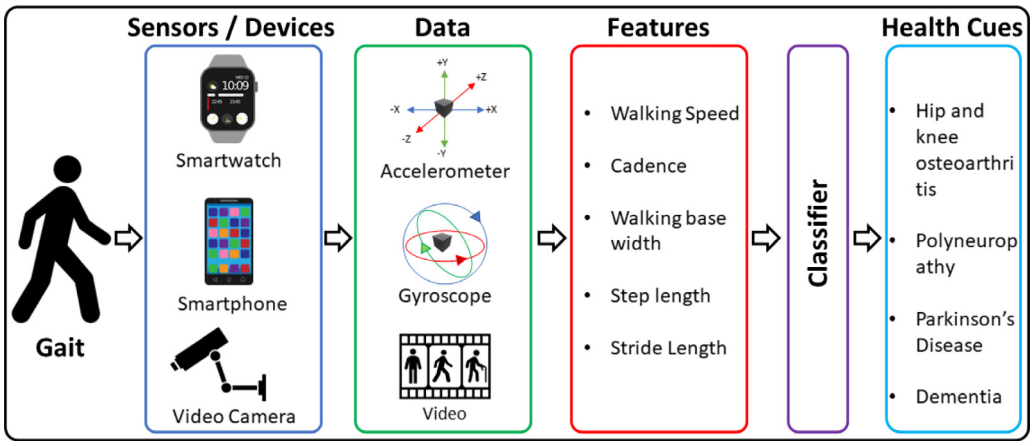


Fig. 9. Deducing health cues from the gait modality.

PD-related motor symptoms. In contrast, in OFF state the medications cannot manage PD-related motor complications. Automatic monitoring and detection of OFF states' occurrence can be crucial for effectively scheduling and adapting the medication intake of PD patients, thus reducing their time spent in the OFF state. One of the recent works in this direction (Pompili et al., 2020) combined MFCC and eGeMAPS-based speech features with Deep Neural Networks (DNN) to classify the medication state of PD patients from their speech, thus potentially serving as a health monitoring tool for PD patients.

Automatic detection of disorders such as depression, anxiety, and diseases such as Parkinson's, as discussed previously, can usually be done using voice samples alone. However, recent research has explored integrating data from multiple modalities to improve detection performance for such disorders. For example, in Nasir et al. (2016) authors develop a multimodal depression classification system based on speech and facial landmark features. In another work (Vásquez-Correa et al., 2018), a group of researchers successfully developed a multimodal system for detecting Parkinson's disease by supplementing speech data with handwriting and gait. This suggests that multimodal biometric data can potentially reveal more health cues than single modality data.

5. Gait modality

Gait is a behavioral biometric modality that identifies people based on their unique walking pattern (Connor and Ross, 2018). While most biometric gait recognition systems use video cameras to record and analyze each body part's motion (Nonnekes et al., 2020), some recent works also use a wearable accelerometer and gyroscope sensor to perform gait recognition (Zhang et al., 2012). Apart from serving as a biometric modality for identity, gait is now also being used to diagnose and monitor an individual's physical and psychological well-being. Gait is particularly well-suited for diagnosing and monitoring diseases such as osteoarthritis (Pirker and Katzenschlager, 2017) and Parkinson's disease (PD) (Barth et al., 2011; Nonnekes et al., 2018) that affect the initiation and coordination of human movement patterns (see Fig. 10). Therefore, gait-based biometric recognition systems can be used to monitor any deviation from the normal gait of an enrolled user to help early-detect any underlying health conditions associated with the deviation. Furthermore, gait analysis can also be performed to track the evolution of an existing health condition and help adapt the treatment to fit the user's changing condition.

Gait disorders can be linked to a wide gamut of physiological and psychological ailments, thereby broadening the scope of gait analysis-based healthcare services. However, it is important to note that gait, unlike other biometric modalities such as face and fingerprint, is a behavioral modality influenced by age, emotion, and socio-cultural factors (Pirker and Katzenschlager, 2017). Therefore, it is essential to disambiguate the changes in a person's normal gait caused by non-ailment related factors, such as age and emotion, compared to the changes influenced by underlying ailments.

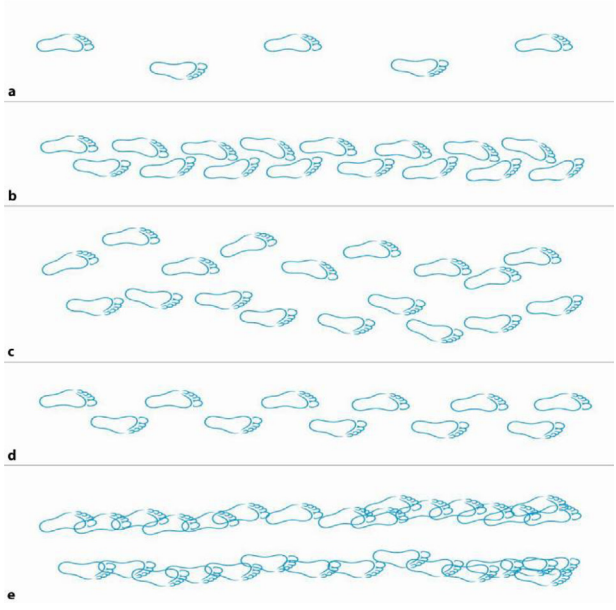


Fig. 10. The above image taken from Pirker and Katzenschlager (2017) shows an illustration of the step sequence in the following gait conditions: (a) normal gait, (b) spastic paraparetic gait, (c) cerebellar ataxic gait, (d) parkinsonian gait and (e) frontal gait. Note the differences in step width, stride length and foot rotation across the different gait conditions.

Gait analysis for healthcare applications is mostly done using specialized medical-grade gait sensors and human experts. However, recently, a wide variety of automated machine learning techniques (Barth et al., 2011; El Maachi et al., 2020) have been proposed to perform gait analysis using cheaper consumer-grade sensors, such as video cameras, accelerometers, and gyroscope, found in smartphones and smart wearables. This reduces the entry barrier for the development of affordable and accurate gait-based smart healthcare devices. Authors in Barth et al. (2011) developed sports shoes equipped with inertial sensors (gyroscopes and accelerometers) to distinguish mild and severe gait impairment caused by Parkinson's Disease (PD). The authors used Boosting, Linear Discriminant Analysis (LDA), and Support Vector Machines (SVM) to identify PD-related gait impairments from the accelerometer and gyroscope data. In a similar work (Juen et al., 2014), the authors developed a smartphone application for leveraging the accelerometer built into modern smartphones to record the phone owner's

Spatio-temporal motion data and detect any unhealthy gait patterns using Support Vector Machines. Furthermore, the authors demonstrate their application's superior performance compared to medical-grade pedometers for detecting chronic heart and lung disease, including congestive heart failure and especially chronic obstructive pulmonary disease (COPD).

Gait as an indicator of overall health is especially useful in the elderly demographic due to its ease of collection. Furthermore, increased life expectancy due to improved medical technology and healthcare systems has projected a significant rise in the aging population worldwide (Majumder et al., 2018). Therefore, it is essential to develop affordable, non-invasive, easy-to-use, and reliable gait-based healthcare solutions that can be easily and cost-effectively deployed at a mass-scale. Following this motivation, authors in Majumder et al. (2018) developed a low-cost, non-invasive gait analyzer to quantitatively identify the healthy gait corresponding to a given gender and age group. The authors can thereby evaluate an individual's gait compared to the baseline characteristics of their peer group. The proposed gait analyzer uses low-cost, wireless, and miniature micro-electromechanical sensor-based inertial motion sensors to obtain acceleration and angular velocity of walking from both legs. Furthermore, the authors used a discrete wavelet packet analysis to extract a set of temporal, statistical, and energy-based gait characteristics. These gait features were later analyzed for potential gait disorders using a support vector machine-based machine learning model.

Although a majority of the research in biometrics uses face, ocular, voice, and gait modalities for gleaning health cues, some work has been done using the fingerprint and handwriting modalities also. One of the most prominent fingerprint-based health indicators, ironically, is its absence. The absence of fingerprints can indicate disorders such as adermatoglyphia (Sabbir, 2020) and dermatitis (Mirsky, 2020). It may also indicate that the individual is receiving capecitabine-based anticancer treatment (Al-Ahwal, 2012; van Doorn et al., 2017). Handwriting patterns (signature verification and keystroke dynamics), similar to the gait modality, are considered behavioral biometric identifiers. One of the most prominent applications of handwriting patterns in this regard is for detecting Parkinson's and other neurodegenerative disorders. The changes in the spatio-temporal (stroke's path length, movement time per stroke) and kinematic (trajectory during handwriting, rate of change of acceleration resulting in jerk) characteristics of a person's handwriting are known to be related to various neurodegenerative disorders (Vessio, 2019).

6. Challenges

The advent of affordable and reliable biometric sensors in consumer devices, such as smartphones and smartwatches, has made biometric-based applications an integral part of our daily lives. Furthermore, the data captured by biometric sensors carry ancillary information, such as age, sex, and even health cues. These health cues can be efficiently extracted from the biometric data to develop affordable and reliable healthcare applications. One such example is deployed in Tufts Medical Center, where facial analysis has been used for over two years for evaluating pediatric patients for genetic disorders (Tufts Medical Center, 2020). However, the performance of these systems relies on the availability of good quality and unbiased data samples from a large number of subjects. Any imbalance present in the training data can lead to a bias in system performance, particularly for data-driven deep learning-based models. For example, Face2Gene, a tool for detecting Down syndrome (trisomy 21) from face images, performs better on images of Caucasian subjects compared to images of African subjects (Lumaka et al., 2017). This performance bias resulted from a greater proportion of Caucasian subjects in the training data of Face2Gene. Furthermore, the inclusion of some African descent images in the training data significantly improved the Face2Gene's performance on images of African descent, thus validating the importance of balanced datasets to develop such tools. While the health care application of biometric data showcases the versatility of the latest machine learning techniques (e.g., Deep Learning), it also raises several privacy concerns for the potential misuse of such technology for unethical and even illegal applications. For example, insurance companies may analyze a customer's face images to assess their health conditions before offering (or even denying) them insurance coverage. Therefore, any application of such technology should be used responsibly and adhere to appropriate privacy-protection laws. Furthermore, privacy-preserving schemes, such as a semi-adversarial network (SAN) (Mirjalili et al., 2020), can be used to deliberately perturb the biometric data to suppress/control specific personally identifiable information, such as age, gender, and ethnicity, to prohibit the use of the data for any other purpose without the owner's consent. Similarly, joint learning and unlearning to retain primary classification functionality (e.g., age classification) while ignoring secondary or spurious classifications (e.g., gender and ethnicity classification) can also aid in privacy preservation (Alvi et al., 2018). Another aspect that warrants caution is the reliability of the predictions generated by the automated classifiers. Facial affective computing has seen a surge due to commercially available facial expression classifiers (Dupré et al., 2020). The emotions associated with the predicted expressions can be further used for deducing psychological/psychiatric disorders. However, as indicated in Heaven (2020), the variation in facial expressions across contexts and cultures may hinder the universal depiction of an individual's mood.

7. Summary

Biometric data is primarily collected to establish or verify an individual's identity. However, it can also reveal potential health conditions of the concerned individual. For example, the presence of specific facial phenotypical variations captured in face images can indicate a probable genetic disorder. Similarly, other biometric modalities such as ocular, gait, and voice also contain health cues indicating the presence of a wide variety of physiological and behavioral health disorders. Furthermore, specialized machine learning-driven methods have been developed for reliably extracting certain health cues from biometric data. In this paper, we reviewed different health cues embedded in audio-visual biometric data. We also discussed various machine learning techniques that have been developed or appropriated for gleaning these health cues from the biometric data and associating them to possible health disorders or diseases at the source. We also discussed several challenges, such as poor quality and biased data samples, associated with using biometric data for diagnostic applications. Finally, we also discussed several privacy concerns for the potential misuse of the information regarding health conditions gleaned from biometric data for unethical and even illegal applications.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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