ANALYSIS OF MODERN INTELLIGENT TECHNOLOGIES IN COMPUTER DIAGNOSTICS IN THE CONTEXT OF SUPPORTING SUSTAINABLE DEVELOPMENT GOALS

Dmytro Prylepa
Ph.D. of Technical Science, Sumy State University, Ukraine
ORCID ID: 0000-0002-4022-5496

At the current stage of societal development, changes caused by the integration of digital technologies into various spheres of human activity are observed not only in industries that use high-tech equipment but also in fields traditionally considered less susceptible to the application of technology due to their nature, as well as in the arts, humanities, education, and healthcare.

Computerization is currently a key vector of industrial development, a cause and source of changes that affect processes or aspects of various spheres of human life and activity. In addition to national trends that define the directions of development in individual countries, determining their national-cultural specifics, state policies, and the level of science and technology, there are also global trends of an intersectoral and supranational nature. One such trend is the use of the potential of high-tech solutions and knowledge-intensive technologies to enhance the quality and personalization of healthcare services. The use of information technologies in healthcare in the 21st century is the foundation for the development of medicine and the growth of the medical goods and services market. Thanks to computerization, the effectiveness of existing diagnostic and therapeutic methods is increasing, leading to the development of new medical IT solutions and the establishment of personalized and predictive approaches in medicine. The use of digital technologies in medicine can be viewed as a process that occurs on two interconnected levels: the provision of medical services and the development of new methods and tools. Modern internet technologies allow for improving both quantitative indicators (reducing time and costs for patient examination and treatment) and qualitative indicators (increasing the accuracy of diagnosis and treatment effectiveness).

Since medicine is a field governed by very strict ethical standards, the ability to conduct trials and validate medical decisions through computer and virtual modeling is of great importance. It is important to emphasize that legal responsibility for the results of diagnosis and treatment lies directly with the doctor. Computer modeling of medical devices and instruments reduces development and manufacturing costs by creating more accurate performance characteristics and conducting virtual tests on computer models.

Processing and analyzing large data sets obtained through Big Data technology [1–3] allows for improving the reliability of disease progression forecasting, taking into account the physiological and genetic characteristics of the patient to adjust the treatment plan. A promising approach for securing and quickly accessing medical information is the use of blockchain technology [4, 5]. Thus, the processing of large data sets using artificial intelligence systems enables personalized treatment, analyzing data from complex medical examinations, and identifying promising directions for scientific research.

With the onset of the computer era, electronic health records (EHRs), online bibliographic databases, and clinical pathway flowcharts became widely used in real-world practice [6–8]. Electronic records have changed the way healthcare facilities operate by centrally storing all patient records, ensuring instant access for medical staff, and improving interaction between doctors and patients. From the very beginning, EHRs were developed and used in both inpatient and outpatient healthcare institutions, but EHRs today are still a hybrid collection of computerized and paper-based data. Alongside EHRs developed with hierarchical or relational databases, clinical systems such as COSTAR, PROMIS, TMR, and HELP have found widespread application in recent years, developed to improve medical care and be used in medical research [9, 10]. Regardless of how EHRs were developed, whether on minicomputers or large mainframes, removable disks were used to address data storage issues and for additional storage and database backup [11].

The emergence of affordable, powerful, and compact hardware, personal computers, local networks, and the internet provided quick access to medical information and initiated the use of web-based EHRs [12]. At the initial stage, key tasks included developing an intuitive user interface for EHRs [13] and adapting it for portable computers [14], which were later classified as netbooks, laptops, and mobile devices [15].

The increasing number of third-party applications used in EHRs required the development of additional and specific interfaces, making it clear that standards needed to be adopted. By 1992, the main standards for the interface between EHRs and vendors for interaction with other systems were HL7 and IEEE P1157 [16, 17]. The advantage of this approach was the reduction of ambiguity in the definitions of data elements.

Modern EHRs do not meet the needs of current distributed systems and the rapidly changing healthcare environment [18, 19]. The ability of programs to transmit and intelligently process complex healthcare information has become paramount [20]. A significant part of EHRs implementation continues in an environment shaped by paper-chart thinking, which continues to limit progress [21]. Further research is needed to understand the factors of human-technology integration that may lead physicians to continue relying on paper-based EHRs alternatives [22].

In the 1970s, based on earlier cognitive research, the first diagnostic and treatment expert systems were developed, with MEDLINE being a classic example. These expert systems aimed to capture doctors' experience and simulate complex medical diagnostic or treatment procedures [23, 24]. However, the primary drawback of this entire class of expert systems is their inflexibility, leading to the rapid "aging" of their knowledge base and lagging behind the continuous and rapid development of diagnostic and treatment methods and equipment.

One of the key areas of healthcare digitalization is telemedicine—the remote provision of medical services, such as primary diagnostics and comprehensive health monitoring, consultations, self-diagnosis, and self-monitoring through specialized online services and applications. Telemedicine requires the development and implementation of specialized platforms for collecting information and integrating information systems from different medical institutions into a single network [25]. These platforms or networks are responsible for collecting, storing, managing, and transmitting personal information between information systems. Therefore, it is crucial to ensure data and document security. This task can be addressed through blockchain technology.

The diversity of blockchain projects—both in development and those already in use—indicates that IT solutions based on this technology are in demand in the healthcare sector and are truly necessary [26, 27]. Blockchain-based medical IT solutions are utilized in clinical research [25], in organizations managing and controlling medical documentation [28], optimizing the provision of medical services [29], and regulating the supply of medicines to patients [30].

A promising direction for decentralized EHR storage is the use of blockchain technology (Medicalchain, UK; BurstIQ, USA, and others), which ensures secure storage and authorized access to up-to-date patient data with their consent. Blockchain technologies minimize the risk of intentional alteration or destruction of EHR data. Additional opportunities for EHRs are provided by smart contracts and smart card users (Guardtime, Switzerland), which record each cardholder's visit to a medical institution [31, 32]. The EHR gives the doctor full access to necessary information in the patient's medical records and data from medical devices, as well as results from genomic, pharmacogenomic, exposomic, anatomical, and other data analyses (DeepMind Technologies, USA; Doc.ai, USA) [26]. In addition to providing medical services, blockchain projects utilize emerging technologies that support predictive medicine [31] or focus on creating secure repositories for clinical data suitable for medical trials [25], which are crucial for both scientific and practical applications. Another promising approach to the remote provision of a wide range of medical services is the use of medical robots, including diagnostic and rehabilitation systems, surgical and therapeutic robots, remote patient history management, and more. In addition to telemedicine, medical robotics is being used to provide innovative solutions in prosthetics, patient rehabilitation and care, laboratory research, and personnel training.

The most effective achievement of telemedicine is robotic surgery—the integrated application of robotics, mixed reality, and the Internet to perform surgical operations. One of the first such surgeries was coronary surgery performed by specialists at the Ahmedabad Heart Institute (India) in 2019 [33]. Currently, remotely operated robotic surgical systems are widely used in practical healthcare institutions [34]. These robotic surgical systems have been developed by large companies and startups, such as Renishaw (UK), EndoControls (France), Era Endoscopy (Italy), Rehab-Robotics (Hong Kong), Olympus (Japan), Mazor Robotics (Israel), KUKA (Germany), Elekta (Sweden), and Intuitive Surgical (USA). A robotic surgical system typically includes a control block for the operating surgeon (console and monitor) and an execution block, including manipulators and instruments, with varying numbers depending on the system. The use of medical robots during surgical procedures enhances the quality and safety of these procedures, thereby reducing the time for postoperative rehabilitation of patients [34]. The use of robots for procedures that could negatively impact the health of medical personnel (such as X-rays or working with patients in quarantine) reduces the risk of illness among healthcare workers by minimizing contact with patients, ensuring efficient care [25]. The potential of robotics is also being explored in the production of bionic prosthetics and the development of mechanotherapeutic robots (exoskeletons, exorucks, etc.), which are used in patient rehabilitation to restore impaired functions and compensate for the loss of musculoskeletal functions [32]. Medical robots can also be used for training purposes, acting as trainers. For example, medical simulators are used to train students and staff in the formation of skills related to emergency care and resuscitation.

The integration of digital technologies into medical practice and the healthcare sector largely depends on the ability to obtain data from medical devices and remotely control them, as well as their capability to function autonomously and interact with one another. These capabilities are supported by the use of the Internet of Medical Things (IoMT) technology, which refers to the concept of a computational network of medical devices, sensors, and equipment that interact with each other and with the external environment through data transmission protocols to influence preventive, therapeutic, and rehabilitation processes.

The IoMT devices can be divided into four main categories: diagnostic, preventive, therapeutic, and rehabilitation. The first group includes devices such as digital blood pressure monitors, urine analyzers, ultrasound devices, glucometers, thermometers, and urine meters. The second category encompasses non-specialized gadgets with medical functions, such as fitness trackers, pulse meters, scales with body fat content measurements, heart rate monitors, devices for determining caloric content, and detecting harmful substances in food, among others. Insulin pumps and smart "dots" can also be categorized separately. The final group consists of devices that help with patient rehabilitation and enhance their quality of life after surgery or illness. Diagnostic sensors have found the most practical application in patient monitoring and treatment. Examples include the EarlySense heart monitor (Israel), the wearable Sensor Dot device (Byteflies, Belgium/USA) for predicting epileptic seizures, C-Scan embedded sensors (Check-Cap, Israel) for generating computer images, Proteus Discover patches with sensors attached to the patient's body and used alongside ingestible sensors (Proteus Digital Health, USA) for patient data collection, and others [35]. IoMT systems enable the creation of digital clinics by digitally transforming some of the processes occurring within them, such as monitoring equipment performance, distributing patients to available beds (AutoBed from GE Healthcare, USA), and providing access to electronic patient records, among others [32].

Medicine is a field that requires the collection and processing of large volumes of data: patient examination results; reports on chronic, hereditary, and past diseases and treatment methods; messages received from domestic medical devices and non-specialized gadgets; a significant amount of information comes from medical robotic devices during their operation. The use of medical solutions based on Big Data technology should ensure more accurate and faster diagnostics and the implementation of the principles of predictive medicine: forecasting diseases and complications for their prevention and rapid treatment [36]. The need to collect and analyze even more information to support the effective and coordinated operation of medical organizations is defined by national healthcare policies in Ukraine [37]. At the management level of individual organizations (clinics, outpatient clinics), Big Data technology identifies factors and barriers to improving management effectiveness based on the analysis of staff performance, equipment and system load, such as material and medication costs [38]. At the national healthcare system level, Big Data technology provides the ability to assess the effectiveness of systems as a whole for the entire country or its regions, track the movement of budgetary and extrabudgetary resources, forecast the spread of epidemics and pandemics, and analyze measures for their prevention and delay [39]. At the level of medical science, Big Data technology is used to solve descriptive, diagnostic, and predictive-analytical tasks of varying complexity, including processing data with unclear or non-trivial interactions [40]. The use of bioinformatics methods involves the analysis and interpretation of large experimental databases, as well as the study of genomic data to address clinical tasks related to the diagnosis and search for treatment methods for oncological, genetic, and infectious diseases [41, 42]. The analysis of large data sets and the development of bioinformatics are connected with the use of artificial intelligence, primarily based on machine learning and pattern recognition.

Artificial intelligence (AI) systems enable the recognition and identification of patterns in large datasets, leading to the formation of predictive models [25]; they are used for solving diagnostic tasks and forecasting oncological and cardiological diseases (Watson Health, IBM, USA), ophthalmological conditions (DeepMind Health, Google Health, USA), fetal development pathology (ScanNav, MedaPhor, UK), the diagnosis of infectious diseases using microvisualization of blood samples (BIDMC, Israel), and others [43]. Another direction for the use of AI in medicine is the development, study, and enhancement of pharmaceutical substances, therapeutically significant compounds, and biologically active molecules using computational chemistry, bioinformatics, digital modeling, and algorithmic design methods [25]. Drug design is based on the iterative construction of a neural active molecule with a stable structure and predetermined properties, incorporating various methods that use search algorithms and evolutionary techniques. The first successful example of drug design was the carbonic anhydrase inhibitor dorzolamide, which was approved for use in 1995. Another example is the creation of imatinib, a tyrosine kinase inhibitor developed to block the bcr-abl fusion protein. Digital drug design methods were also applied during the COVID-19 pandemic.

The modern diagnostic process in medicine plays one of the key roles in patient care. When a diagnosis is made in a timely and accurate manner, the patient has the best chances for a positive health outcome, as clinical decisions will be adapted to a correct understanding of the patient's health issue [44]. The diagnostic process occurs within a working system that consists of a diagnostic team, tasks, technologies and tools, organizational factors, the physical environment, and the external environment [45, 46]:

a) The diagnostic team consists of patients and their families, as well as all healthcare professionals involved in their care;

b) Tasks are purposeful actions that occur within the framework of the diagnostic process;

c) Technologies and tools include health information technologies used during the diagnostic process;

d) Organizational characteristics include culture, rules, and procedures, as well as leadership and management considerations;

e) The physical environment includes elements such as planning, distractions, lighting, and noise;

f) The external environment includes factors such as the payment and service delivery system, the legal environment, and the reporting environment.

All components of the working system interact, and each component can influence the diagnostic process. The working system provides the context within which the diagnostic process takes place [45, 47]. There are a number of settings in which the diagnostic process may occur, such as outpatient departments for primary or specialized care, emergency departments, inpatient hospitals, long-term care facilities, and retail clinics. Each of these includes six components of the working system — members of the diagnostic team, tasks, technologies and tools, organizational factors, the physical environment, and the external environment — although the nature of the components may vary across different settings.

The diagnostic process relies on adapting a decision-making model, which describes the cyclical process of information gathering, integration, and interpretation, as well as the formation of a working diagnosis [48, 49]. To this end, the healthcare committee has developed a conceptual model to illustrate the diagnostic process (Fig. 1.1).

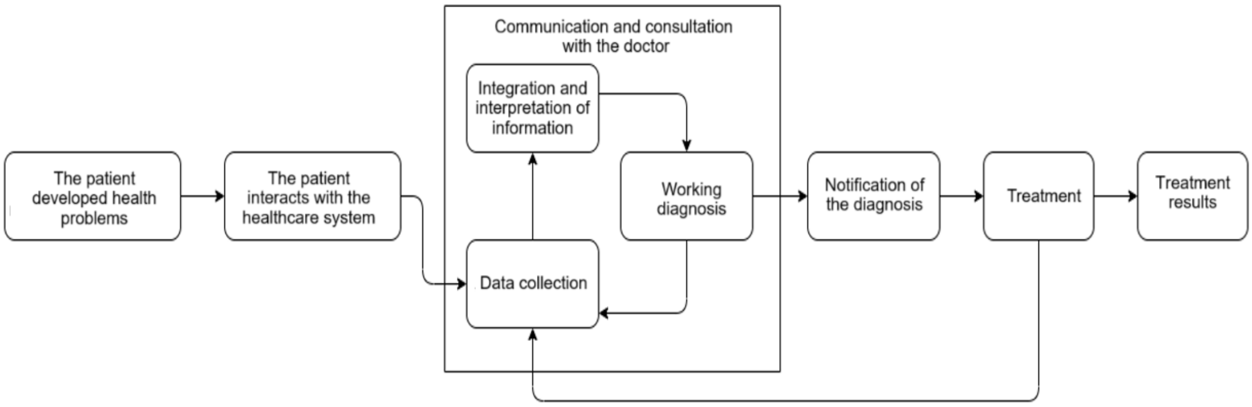

Fig. 1.1. *Diagnostic Process Model*

The diagnostic process unfolds as follows: initially, the patient experiences health issues. The patient is most likely the first person to consider their symptoms and may decide to collaborate with the healthcare system at this stage. When the patient seeks medical help, an iterative process of information gathering, integration, and interpretation occurs, followed by the establishment of a working diagnosis. Collecting the patient’s medical history, conducting an interview, performing a physical examination, diagnostic testing, and referring or consulting with other healthcare providers are ways of accumulating information that may be relevant to understanding the patient's health issue. Approaches for information collection can be employed at different times, and diagnostic information can be obtained in various sequences. The continuous process of gathering, integrating, and interpreting information involves generating hypotheses and updating prior probabilities as more information becomes available. Communication between healthcare professionals, the patient, and the patient’s family members is crucial in this cycle of information gathering, integration, and interpretation.

The working diagnosis can be singular or consist of a list of potential diagnoses. Typically, healthcare providers consider more than one diagnostic hypothesis or explanation for the patient's symptoms and refine this list as additional information is gathered during the diagnostic process. The patient should be informed of the working diagnosis, including an explanation of the degree of uncertainty associated with the working diagnosis. Each time the working diagnosis is revised, this information should be communicated to the patient. As the diagnostic process progresses, a broad list of potential diagnoses can be narrowed down to fewer options, a process known as diagnostic modification and refinement [51]. As the list narrows to one or two possibilities, diagnostic refinement of the working diagnosis becomes diagnostic verification, during which the primary diagnosis is tested for its adequacy in explaining the signs and symptoms, its consistency with the patient's context (physiology, risk factors), and whether a single diagnosis is appropriate. When considering invasive or risky diagnostic tests or treatment options, the diagnostic verification stage is especially important to ensure that the patient is not exposed to these risks without sufficient likelihood that the testing or treatment options will be informative and likely improve the patient's outcomes.

Throughout the diagnostic process, continuous evaluation takes place to determine whether sufficient information has been collected. If members of the diagnostic team are unsure whether enough information has been gathered to explain the patient's health issue or if the available information does not align with the diagnosis, the process of gathering, integrating, and interpreting information, as well as developing the working diagnosis, continues. When the members of the diagnostic team recognize that they have obtained an accurate and timely explanation of the patient's health problem, they communicate this explanation to the patient as a diagnosis.

It is important to note that healthcare professionals do not need to achieve diagnostic certainty before beginning treatment. The purpose of gathering information in the diagnostic process is to reduce diagnostic uncertainty to a level that allows for optimal decisions regarding subsequent treatment [50]. Furthermore, the treatment process may also inform and refine the working diagnosis, as indicated by the feedback loop from treatment back to the information-gathering stage of the diagnostic process. This also highlights the need for healthcare professionals to diagnose health issues that may arise during treatment.

The following four types of information-gathering activities were identified in the diagnostic process: medical history collection and interviews; conducting a medical examination; obtaining diagnostic tests; and referring the patient for further consultation or referral. It is assumed that the diagnostic process has broad applications, including the provision of medical and psychological assistance. In cases where diagnosis is fully or partially carried out by a computerized diagnostic system, assessing the psychological, emotional, or emotional-psychological state of the patient requires the involvement of additional specific algorithms and software-hardware complexes.

In this context, a promising direction is the development of computerized systems and specialized medical equipment capable of recognizing the emotional-psychological state of a person by analyzing factors such as self-report, reaction to fear, behavioral responses, autonomic measurements, neurophysiological measurements, and so on.

In the absence of the possibility to apply specific medical equipment or in cases where real-time diagnosis is needed without prolonged patient observation, the use of modern facial analysis systems is a promising approach [51, 52]. Methods and techniques for detecting and localizing faces in images or videos, identifying a specific person, and classifying emotional states have made significant progress in recent years. Currently, these methods are successfully applied on various devices, such as digital cameras or software applications, like facial recognition on social networks such as Facebook. However, current classifiers have certain limitations. Classifiers are mostly trained using instructed, i.e., artificially expressed, emotions. Instructed facial expressions intended to characterize a particular emotional state in datasets such as Caltech Faces, BaoDataBase, and YALE represent exaggerated situations (unrealistically high levels of the assigned emotion), thus resulting in a lower success rate for these classifiers [53, 54]. For this reason, additional methods for collecting facial datasets were developed to reflect the true emotional state [55]. However, doubts remain regarding the ability of modern systems to classify real feelings and specific emotional states.

Currently, deep learning and predictive analysis methods are being developed in medical diagnostics to help understand the feelings and needs of bedridden patients who are unable to communicate verbally with the doctor [56, 57].

The work [58] demonstrates a new approach that is based not only on facial analysis but also on information from eye movement tracking and probing. Specifically, the authors extracted temporal frequency functions of eye movement by applying short-time Fourier transforms to raw multichannel eye tracking signals. To integrate temporal movements in time (i.e., saccade duration, fixation duration, and pupil diameter), two functional strategies were explored: feature-level fusion (FLF) and decision-level fusion (DLF). Recognition experiments were also conducted based on three emotional states: positive, neutral, and negative. However, the average accuracy was 88.64% (FLF method) and 88.35% (DLF method). Therefore, current methods in this field focus on deep learning and so-called emotional computing. Research oriented towards emotional computing [59, 60] is one such example. In the work [61], Markov chains were used to classify only two emotional states (negative/positive). Thus, the authors created an emotional probability that simulates the dynamic process of spontaneous emotional state transfer. This method offers a new approach to studying emotional state classification, such as emotional computation and the theory of emotion automation generation. In the works [62, 63], a mathematical model of human-computer interaction is proposed for the development of software aimed at facial analysis and emotional state classification. The goal of the mathematical model is to assist psychologists in better understanding, accurately defining, and expressing the essence of natural emotions, especially in decision-making processes.

The work [64] discusses software for accurate recognition and classification of emotional states. The software recognizes emotions from image files or uploaded video files. The program can also use real-time data from a webcam to classify so-called subtle facial emotional expressions. It employs the FURIA algorithm for unordered fuzzy rule induction. This algorithm allows timely detection and return of appropriate feedback based on facial expressions. The success rate of the algorithm is 83.2%.

Thus, the current trend in the development of computerized systems for diagnosing human EPS is the use of modern intelligent information technologies for data analysis based on machine learning and pattern recognition.

Since the development of computerized diagnostic systems in medicine opens up new opportunities for improving medical practice, equally important is the analysis of psychodiagnostics methods, which allow for assessing the psychological state of patients and supporting the diagnostic process on another, psychological level.

The well-known methods of emotional-psychological diagnostics based on observation, surveys, and the analysis of EHR rely on the use of qualitative measurement scales for diagnostic features, which often results in insufficient reliability. Modern psychodiagnostics methods addressing core psychological processes, traits, and states of an individual emerged in the early 20th century within the framework of the behaviorist approach [65]. With the development of probability theory and mathematical statistics, these methods facilitated the creation of scientific approaches to quantitative psychodiagnostics.

A classical example of psychodiagnostics through syndrome detection is the DSM V diagnostic system [66]. This system identifies potential causes of emotional, cognitive, physiological, and behavioral characteristics that lead to specific treatment plans aimed at addressing identified issues. In this process, the psychologist must carefully assess the client's symptoms and critically evaluate how this specific set of symptoms impairs the client's ability to function in daily life. Practicing clinicians often use multiple tools to assist in this evaluation, including clinical interviews, observations, psychometric tests, and rating scales.

The DSM V system serves as a standard reference for distinguishing one type of mental disorder from another and provides specific criteria for classifying emotional and behavioral disorders, outlining differences between various conditions.

The primary goal of psychodiagnostics is to create conditions for corrective and developmental work, generate recommendations, and organize psychotherapeutic interventions. In line with this goal, psychodiagnostics methods are divided into standardized and clinical categories [67, 68].

Standardized psychodiagnostics methods are considered most effective when it is necessary to obtain data from a group of individuals within a short time frame and to make specific decisions based on a quantitative justification of reliability. Standardized methods are protected from various errors that may arise due to the insufficient qualifications of the specialist [67, 69].

Qualitative psychodiagnostics methods tend to be more effective when employed by experienced psychologists, such as those involved in personnel selection or professional assessment. These methods allow for a more detailed and in-depth study of an individual's personality traits. However, their implementation requires a large number of diagnostic indicators [70, 71]. Therefore, professional psychodiagnosticians agree that qualitative methods may be even more effective when the psychologist conducts psychological training, psychotherapy, or psychological correction based on the results of these methods.

In the work [72], a classification was proposed based on psychological research methods: organizational, empirical, experimental data processing methods, and interpretive methods.

According to W. Simon's classification, psychodiagnostics methods can be divided into formalized, semi-formalized, and difficult-to-formalize methods. Each of these methods has its advantages and limitations, so the choice of a specific method depends on the nature of the problem being studied and the objectives of the research. Formalized methods are those that use mathematical models. Semi-formalized methods are realized within an algorithmic approach using quantitative measurement scales.

The semi-formalized group includes methods that utilize the potential of general psychological diagnostic techniques. These methods include activity analysis, diagnostic interviews, observations, etc. The use of such methods requires a high level of expertise, as in most cases, there are no standardized ways of implementing or interpreting the results. Case studies, graphic modeling, and ethnographic methods are key examples of semi-formalized methods [67], and are applied to study complex processes where relationships between phenomena may not always be formalizable.

Hard-to-formalize methods involve the use of qualitative measurement scales [73]. These methods are complex and important tools for evaluating an individual's mental state, enabling the identification of characteristics such as feelings, emotions, relationships, and values that cannot be precisely measured or defined quantitatively. The application of hard-to-formalize psychodiagnostics methods allows researchers to gain a deeper and more detailed understanding of the psychological processes that occur in individuals across different situations. An example of a hard-to-formalize psychodiagnostics method is the phenomenological approach, which is based on the researcher's investigation and description of the phenomena or experiences being studied without the use of standardized tools. The phenomenological approach to psychodiagnostics, as described in [74], enables researchers to gain profound insights into human experience and interpret it in its context. Another example of a hard-to-formalize psychodiagnostics method is the "Depth Interview" method, as discussed in [75]. This method allows researchers to explore the inner world of a person and their psychological experiences by examining their life history.

A notable feature of hard-to-formalize methods is their lack of standardization, which can lead to greater variability in results and difficulties in comparing data between studies and practices. However, hard-to-formalize methods can also be useful for understanding complex psychological phenomena and identifying individual traits of patients. As shown in [76], the use of nonverbal behavior as part of hard-to-formalize methods can be beneficial for detecting mental disorders that may be difficult to diagnose with standardized tests.

Psychodiagnostics methods can vary in their form of administration: they can be individual, group-based, paper-based (written), oral (anamnesis), machine-based (instrumental), computerized, verbal, non-verbal, etc.

If the psychodiagnostics procedure is conducted with one individual, it is termed individual, while if multiple individuals are involved, it is called a group-based method. Both individual and group methods have their advantages and disadvantages. For instance, group methods allow for studying a large number of people, feature more uniform implementation conditions, and simplify the work of the specialist, requiring less time to obtain results. However, their drawbacks include a reduced capacity to establish rapport and understanding with participants and fostering positive motivation toward diagnosing aspects of their personality. In contrast, individual methods do not have these drawbacks but are limited to working with single subjects at a time.

Machine-based (instrumental) psychodiagnostics methods involve the use of specialized technical devices (such as machines and diagnostic apparatus) that operate on mechanical principles to record responses and interpret data. When a computerized method is applied, for example, computer-assisted surveys or testing, the processing of received information is significantly simplified, as is its interpretation, because the data are presented in forms such as tables, charts, diagrams, or graphs. It is important to note that computerized psychodiagnostics allows for the rapid analysis of the obtained data, something that would be impossible with other methods due to the time required. This allows specialists to diagnose the individual characteristics of thinking and determine the pace and other aspects of activity with greater depth.

In recent decades, the science of psychological and emotional states has rapidly developed, achieving significant scientific progress. One of the most important directions in this field is the application of emotion recognition methods to assess a person's mental state through machine learning techniques [77]. Mental states can be assessed using emotion recognition methods based on the analysis of facial expressions, voice, gestures, electroencephalograms, and other internal indicators of emotions and mental states.

It is important to emphasize that emotion recognition methods should not be seen as replacements for psychodiagnostics, as they cannot substitute a deep analysis of personality and its characteristics. However, they can be used as complementary tools for psychological assessment of an individual's mental and emotional state. Emotion recognition methods can help improve the diagnosis of various mental disorders related to emotional states. For example, these methods can be useful in diagnosing different forms of depression, anxiety disorders, autism, and other conditions. Furthermore, they can assist in evaluating the effectiveness of therapy and identifying the patient's need for additional support.

The connection between induced emotional states and characteristic facial expressions has been explored in the works of [78–82]. For example, Charles Darwin suggested that emotional expressions are multimodal behavioral patterns of an individual, forming detailed descriptions of more than 40 emotional states [83]. Over the last century, several psychological models for classifying emotions have been proposed, from general basic emotions to unique and complex ones. Two of the most studied emotion recognition models [84–87] have been primarily used in the last decade: Ekman's six basic emotions classification [88] and Russell's circumplex model of emotion [89].

In contrast to Ekman's classification, Russell's model is less strictly divided, indicating that human emotional states are dynamic multimodal behavior models. For instance, the expression of fear on the face includes pupil dilation and the contraction of muscles around the mouth. Russell's circumplex model suggests that under certain conditions, certain features might overlap and allow the classification of emotions (e.g., joy and surprise, fear and sadness, etc.). Recently, many authors have pointed out that to classify different emotional states, it is necessary to recognize that emotions are expressed through changes in physiological processes [90, 91]. As a result of these changes, various approaches [92, 93] have been proposed to detect responses to specific conditions in individuals, such as behavior, physiological, and empirical components [94].

Modern facial analysis systems capable of determining emotional states based on facial expressions work in three main phases, as defined by Kanada [95]:

- Face detection phase;
- Feature extraction phase;
- Emotion classification phase according to the chosen model.

Interest in this area dates back to the 1960s, when Bledsoe, Helen Chan, and Charles Bisson created the first facial recognition algorithm [96–99]. Their approach and technique were later used by Goldstein, Harmon, and Lesk for the feature extraction phase [100]. The first fully functional system was implemented by Kanada in 1973 [82]. The algorithm could automatically evaluate 16 different facial parameters by comparing extractions obtained through an opto-electronic system. At the time, the system achieved correct identification with a success rate of 45%–75%.

In 2002, Yan introduced a classification [101], which has been widely used by other researchers. It consists of methods based on knowledge, characteristics of invariant approaches, template-matching methods, and methods based on external appearance. Methods for evaluating knowledge levels by determining the emotional and psychological states of students have also been explored [102–104]. Studies on invariant approaches were conducted by Vezhnevyets [105]. Lakshmi and Kulkarni [106] additionally used information about facial skin color to improve detection accuracy by combining it with the gray edge of the input image. Ghimire and Li [107] and Chavhan et al. [108] proposed a new algorithm using image transformations via histograms, with preprocessing and a combination of skin color and image information to improve facial detection speed and verify candidate landmarks (nose, eyes, mouth).

Among the oldest methods based on template comparison is the algorithm proposed by Sakai [109], which used several sub-templates for the eyes, nose, mouth, and face to create an accurate facial model. Later, researchers developed various templates using predefined models [110–113]. Wan and Tan [114] proposed a procedure using an ellipse as a template to describe the face and its parts, which became inefficient over time due to factors like varying face sizes, gaze fixation, or potential face rotation during detection.

Methods focused on appearance stem from template-matching techniques, but for detecting and recognizing specific areas of interest, statistical analysis or machine learning is used. Given the large amount of data that must be processed for these methods, the general approach is to reduce the size of the detected area (dimensionality reduction). Among these methods, some of the most well-known are the AdaBoost algorithm (Viola-Jones detector), the S-AdaBoost algorithm [115], the FloatBoost algorithm [116], hidden Markov models, Bayesian classifiers, support vector machines (SVM), and neural-like structures.

Based on the analysis of various psychodiagnostics methods, it can be concluded that a comprehensive approach is necessary for studying mental states and processes. It was found that each method has its own advantages and disadvantages, so it is advisable to use them in combination with other methods, which will allow for a more complete and accurate picture of a person's EPS. It was also discovered that a significant number of methods have an empirical foundation and require further verification of their reliability and validity. To increase the accuracy of the results, it is important to carefully follow methodological recommendations and consider the individual characteristics of each research subject. Therefore, using a comprehensive approach and adhering to methodological principles will provide more precise and reliable results in psychodiagnostics, which is crucial for further studying and assessing an individual’s emotional and psychological state.

Considering the importance of psychodiagnostics methods for assessing the psychological state of patients, equally significant is the development of machine learning and image recognition technologies, which open up new opportunities for automating and enhancing diagnostic processes in various areas of medicine.

Face recognition is one of the first practical tasks that served as a stimulus for the development of object recognition theory. Face and emotion recognition is applied in various fields of human activity. This area began to develop in the early 1980s, but its growth accelerated in the 1990s during the creation of information retrieval systems for face recognition for identity verification.

Facial recognition from images is one of the most challenging problems in tracking systems research due to various issues [117]. Among these problems are arbitrary initial conditions in image formation, as well as various non-standard factors that influence EPS. A simple change in lighting can be a frequent problem leading to misclassification. Thus, the reliability of recognition methods largely depends on the system's ability to analyze faces in low-quality images.

The machine face recognition process is shown in Figure 1.2.

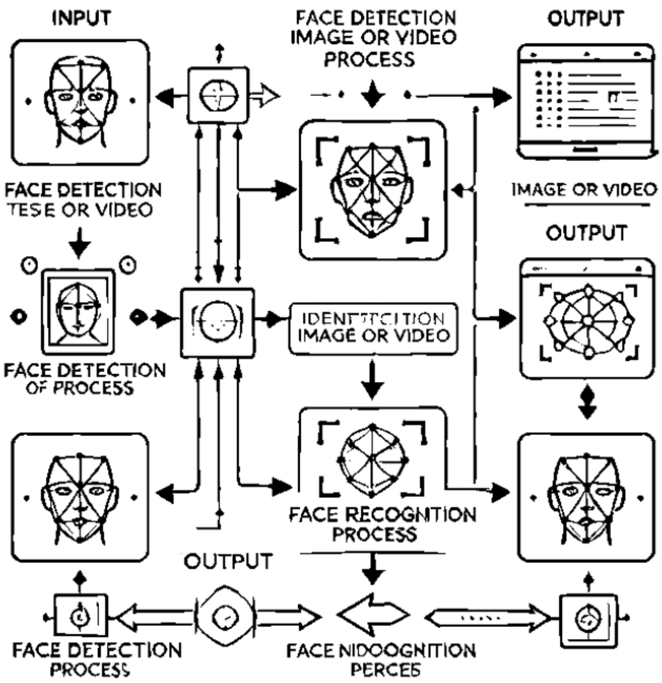

Fig. 1.2. *Face Recognition Process*

There are several methods used for detecting a person's face. They are shown in Figure 1.3 [118, 119].

In model-based techniques for face recognition, strategies are used to develop a model of a person's face, which extracts facial features [120]. One approach to using model-based techniques involves creating a face model by dividing it into separate parts, such as the eyes, nose, mouth, and others, and creating a model for each part individually. Then, machine learning algorithms are used to classify each facial part and compare it with other faces. These strategies have made the recognition invariant to lighting, size, and alignment. Moreover, these methods have other advantages, such as fast matching and compact image representation. The main disadvantage of this model is the high computational complexity of the face recognition method [121].

For face recognition using 3D strategies, optical-electronic sensors are used to capture data from the face. This model is divided into two main types: 3D-position estimation and 3D face reconstruction [122]. The work [123] presents a "New 3D Transformed Model Based on Albedo (AB3DMM)". In the proposed method, lighting normalization was applied during the preprocessing stage to remove the lighting component from images. The results of this study achieved an 86.76% recognition rate on the Multi-PIE database, which was used to evaluate SSR + LPQ. Additionally, the work [124] indicates that 3D facial landmarks were projected as a mesh on a 2D image and then aligned semantically by five facial landmarks of the corresponding images to match the face with a general 3D model.

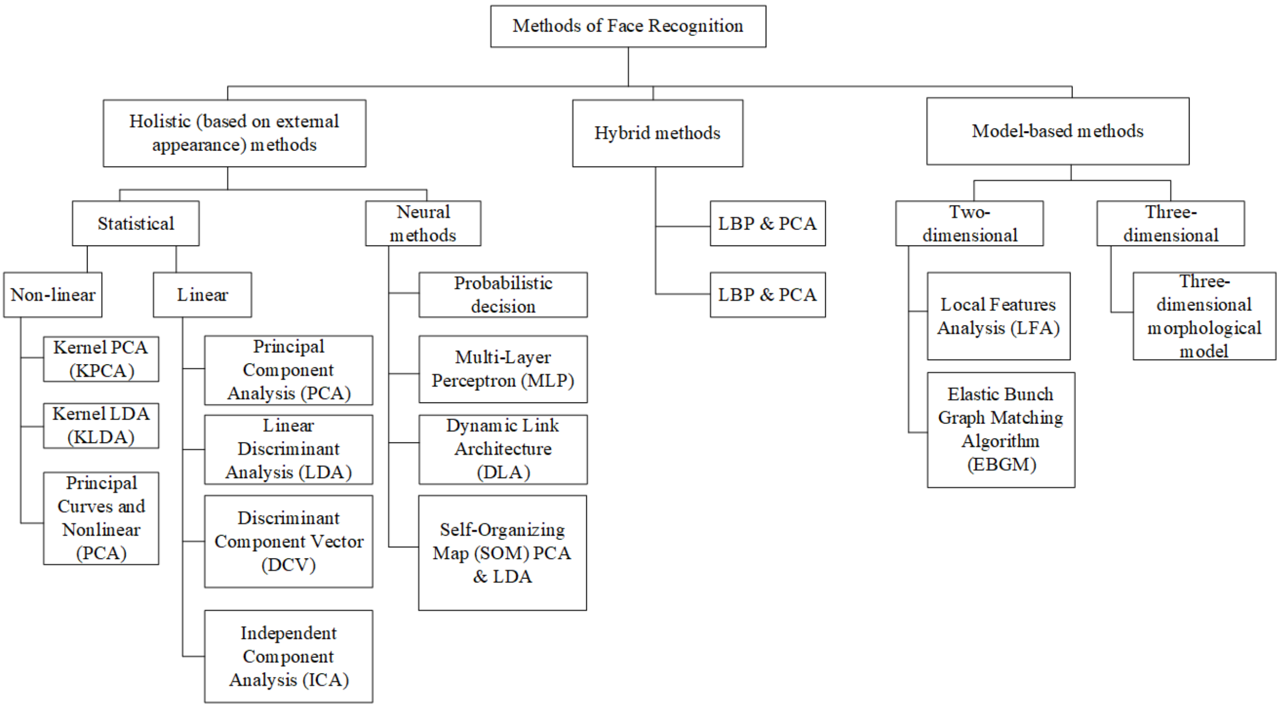

Fig. 1.3. *Approaches to Human Face Recognition*

The Elastic Bunch Graph Matching (EBGM) algorithm is a face recognition method based on comparing a new face image with other faces in a database. The algorithm process begins by extracting object component vectors using the Gabor Jets method, which helps identify key points on the face and obtain information about their orientation and frequency. The extracted elements are then compared with corresponding elements from other faces in the database using the elastic bunch graph matching method. EBGM is an effective method for face recognition under various conditions, such as changes in lighting, poses, and facial expressions. The use of the Gabor Jets method improves the quality of key point extraction and information retrieval from faces. However, the EBGM algorithm has some limitations, such as low speed and relative complexity of implementation. Another drawback is the need for a sufficiently large face database for comparison [124, 125].

Holistic (external) methods are based on a global representation of the face instead of a local representation of the entire image for face identification. This model takes into account the global features of a given set of faces during the face recognition process. The model is divided into three main subspaces: statistical (linear (e.g., PCA, LDA, and ICA) and nonlinear (e.g., KPCA)), neural (e.g., DLA, MLP), and hybrid (e.g., PCA with DLP) [125, 126].

Turk and Pentland were the first to use PCA for human face recognition [127], and face reconstruction was carried out by Kirby and Sirovich [128]. This strategy helped reduce the dimensionality of the input data by extracting the principal components of the multidimensional data [129]. Lighting normalization is crucial for Eigenface. Instead of Eigenface, Eigenfeatures, such as eyes, nose, mouth, cheeks, etc., are used. The computation of the low-dimensional subspace representation is employed for data compression [130-132].

In the work [133], three experiments were presented to enhance PCA efficiency by reducing computation time while maintaining performance. The results showed that the accuracy remained the same in the second experiment, with reduced computation time. According to this approach, the computation time is reduced by 35% compared to the original PCA method, especially with a large database. In the work [134], a new face recognition system for face identification and verification using various distance classifiers with PCA was proposed. This method was applied in the ORL database. Experimental results showed that PCA demonstrated improved results using Euclidean distance classifiers and quadratic Euclidean distance classifiers. When using Euclidean and quadratic Euclidean distance classifiers, the recognition speed was the same. Additionally, in the work [135], several methods for invariant lighting were explored, and a powerful method for face recognition, which works better with PCA, was identified. Furthermore, the work [136] presents a system using PCA-BPNN with DCT. In this method, PCA is combined with BPNN, and from the face recognition perspective, the technique easily distinguishes human faces. Moreover, human face databases are compressed using DCT. The recognition rate of this method exceeds 90% compared to the Face94 and Grimace databases.

Hybrid face recognition methods are approaches that combine several face recognition methods to improve accuracy and reduce errors. One of the popular hybrid methods is the combination of deep neural networks and Principal Component Analysis (PCA) [137]. In this approach, the Karhunen-Loève decomposition method is used for dimensionality reduction of the image, while a deep neural network is used for classification. This approach provides high accuracy and recognition speed. However, its disadvantage is the requirement for a large amount of training data.

Another hybrid method is the combination of Principal Component Analysis (PCA) and Local Binary Patterns (LBP) [138]. In this approach, the PCA method is used for dimensionality reduction of the image, while the LBP method is used to detect local features on the image. This approach provides high accuracy and ensures robustness to changes in lighting and facial poses. However, it may be sensitive to changes in the image background.

The third hybrid method is the combination of LBP methods and the Principal Component Method based on Geometric Functions (G-PCA) [139]. In this approach, the G-PCA method is used to model geometric changes in the face, while the LBP method is used to detect local features on the image. This approach provides high recognition accuracy and resilience to changes in lighting and facial poses. However, it requires additional time for image preprocessing and may be vulnerable to changes in the image background.

Thus, the advantages of hybrid face recognition methods lie in their ability to provide higher accuracy and robustness to changes compared to individual recognition methods. Additionally, combining different methods helps improve the performance of recognition systems in various conditions. However, the downside of hybrid methods is the requirement for a large amount of training data and additional time for image preprocessing. Moreover, selecting optimal combinations of methods can be challenging.

Independent Component Analysis (ICA) represents a linear combination of statistically independent data points [140]. This analysis is aimed at solving the Blind Source Separation (BSS) problem by decomposing the observed signal into a linear combination of unknown independent signals [141, 142]. The work [143] presents a human face recognition system using PCA-ICA and neural network training, such as hybrid feature extraction. This method extracts invariant face features, implementing a face recognition system based on PCA/ICA to create an advanced and reliable human face recognition system. Furthermore, in the work [144], it was demonstrated that the cost function is reduced to maximizing the independence of the extracted objects and the sum of mutual information between the extracted objects and the target variable. Global feature extraction is based on boundary information, while local features are based on modular ICA. Therefore, the new method of feature extraction will guide future research directions in the field of biometrics.

The Hidden Markov Model (HMM) for face recognition automatically divides the face into different regions, such as the eyes, nose, and mouth [141, 145]. The research presented in [146] introduces small facial pixels taken as blocks, and discrete cosine transform (DCT) is applied to these blocks. Moreover, dimensionality reduction using the PCA algorithm directly makes the method very fast. The experimental results show that the recognition rate obtained using this method is 95% when using half of the images for the training set from the ORL database.

The main idea of the Kernel Principal Component Analysis (KPCA) method is to first map the input space to the object space using a nonlinear mapping and then compute the principal components from the object space. Additionally, KPCA requires solving the eigenvalue problem, which does not require additional optimization [120]. The work [147] proposes a new method for feature extraction and processing facial expressions. In this study, a polynomial kernel was successfully used. For classification, they used Euclidean distance classifiers and k-nearest neighbor. The experimental results were similar to those obtained by traditional PCA-based methods. The work [148] presents a comparison of Gabor-PCA and Gabor-KPCA variants to show the performance differences between them. The results showed that Gabor-PCA was more successful than Gabor-KPCA by 6.67%, 0.83%, 12.00%, and 4.17%, using Euclidean, cosine, Manhattan, and MARCOS distances, respectively, based on the ORL database.

Linear Discriminant Analysis (LDA), also known as Fisherface, uses a supervised learning method that applies more than one training image for a single class. This method seeks linear combinations of features while preserving the class by itself. Additionally, it tries to model the differences between different classes. The LDA algorithm is less sensitive to lighting, different poses, and expressions. In [149, 150], decomposition of the sample image and its transposition were performed using the Lower-Upper (LU) decomposition algorithm. Subsequently, the projection space was evaluated using Fisher's Linear Discriminant Analysis (FLDA). Finally, Euclidean distance was used as the classifier. This method was applied to the FERET, AR, ORL, and Yale B databases, resulting in better performance. However, in [151], a classification method was proposed that uses distinct Gabor features and the reliability of ordinal measures based on Fisher's Kernel Discriminant Analysis. Each feature vector, considered as a feature vector, is the input feature for the proposed multiclass KFD classifier based on the RBF kernel. The results obtained on the ORL and Yale University databases showed that performance improved by 88.8% compared to LDA (33.3%).

The Kernel Linear Discriminant Analysis (KLDA) method consists of nonlinear forms for any method. Moreover, the use of kernel functions that satisfy Mercer's theorem is more efficient and economical [152]. In the work [153], Histogram of Oriented Gradients (HOG) and Support Vector Machine (SVM) methods were used as classification methods. The result showed good recognition speed. In [154], HOG and PCA methods were used. The proposed method first extracts features at different scales using the HOG method; then PCA is applied to these feature vectors for dimensionality reduction. The experimental results show equivalent recognition speed at a very small size with low resolution, where facial details are hard to distinguish.

Biometric recognition systems based on human faces use multiple databases during operation. The database shows the "normal" variability in facial expressions, resolution, pose, gender, age, lighting, background cosmetics, photography, appearance, accessories, and occlusions [121]. Below are some of these databases:

The Face94 database contains 153 images of people taken under different conditions — wearing glasses, with various poses, lighting, and facial expressions. Each image is 180 by 200 pixels in size. The database contains image directories separately for women and men, without images of the opposite sex. These data have been used in research to develop and evaluate the effectiveness of various face recognition methods [121, 155].

The FERET database images are divided into two sets: gallery images and probe images. The images in the gallery part have known labels, while the images in the probe part are matched to gallery images for identification [156].

The ORL database contains 40 different individuals (subjects) with 10 images per person. The resolution of each image is 92x112 pixels, and the file format is PNG [121, 157].

The Yale University database consists of images of 10 people recorded in 9 poses under 64 different lighting conditions [121, 157].

The Indian database contains JPEG images of people's faces in 24-bit RGB format, with a resolution of 180x200 pixels. There are 20 individuals, each with 20 images. All images have a bright, uniform background with various angles of the person's face [158, 121].

Thus, the analytical review of face recognition methods allows us to establish the main approaches and algorithms used in this field. Specifically, methods used for face recognition in images were discussed. The methods for face recognition in video were also examined, which allow for determining movements and emotions based on changes in the face. The main challenges related to this task, such as changes in lighting and face position, were analyzed, and methods that reduce the impact of these factors on recognition accuracy were discussed.

Considering the importance of applying machine learning and image recognition technologies to automate diagnostic processes, the next step is a detailed analysis of the research object and the justification for choosing methods for diagnosing the emotional and psychological state of patients.

Human EPS diagnosis can be considered as an intersection of the fields of psychology, artificial intelligence, and information technology (Figure 1.4).

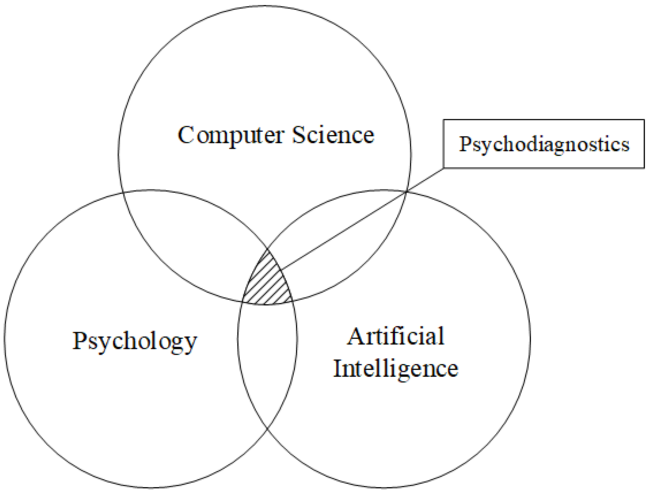

Fig. 1.4. *Diagram of the intersection of scientific fields in psychodiagnostics determination*

The main focus of works on decision-making processes in EPS diagnosis is the development of new, more accurate, and faster methods of non-verbal diagnosis, characterized by high adaptability to the individual features of each patient. This approach ensures the personalization of the diagnostic process and further treatment. At the same time, the necessity to provide the possibility for widespread and mass application of such diagnostics in real-time, without the need for additional specialized equipment, is considered.

Given the inherent high level of subjectivity of the person being diagnosed, the object of study, according to W. Simon, is considered weakly formalized and requires modeling of the decision-making process under conditions of data uncertainty and arbitrary initial conditions for forming the input information description of the human EPS diagnostic system. This process involves studying various features related to the emotional state, particularly facial expressions, which help understand a person's condition. Since the diagnostic process is based on arbitrary initial conditions for image formation, it requires the specialist to have high professional training and significant practical experience to achieve highly reliable results in analyzing large volumes of data with significant overlap in the diagnostic feature space of recognition classes. Overall, human EPS diagnosis is a complex task, and a promising direction for its solution is the application of ideas and methods from machine learning and pattern recognition [159].

The solution to the task of diagnosing human EPS is related to the necessity of overcoming a number of scientific and methodological challenges, the main reasons for which are:

1) Subjectivity of assessment: The assessment of emotions can be very subjective, as different researchers may have different approaches to interpreting a person's emotions and mood. As a result, it can be difficult to obtain the same results across different studies.

2) Standardization of input data: For example, when diagnosing EPS solely based on facial images, people may vary in skin color, head shape, hair, age, etc. Therefore, image standardization is necessary so that emotional expressions can be evaluated uniformly across different images.

3) Limitations of input data: For example, when diagnosing EPS based solely on a person's facial image, it may not reflect the full picture of the person's EPS, as information about context, facial expressions, and gestures may be limited. As a result, it is important to consider that a person's actual emotional state could be more complex than what can be inferred from their facial image.

4) Distortion of results: Research results may be distorted due to various factors that can affect a person's emotional state. For instance, if a person was previously placed in a challenging emotional environment, their emotional state may be skewed when evaluating their emotions based on a facial image. Other factors, such as lighting and the angle of the image, can also influence the results.

5) Insufficient accuracy: Evaluating emotions based on facial images may not be sufficiently accurate, as there are certain emotional expressions that can be difficult to distinguish from one another. For example, mild confusion between sadness and anxiety can lead to inaccuracies when assessing a person's EPS.

6) Interaction with other factors: A person's emotional state can be influenced by other factors, such as stress levels, fatigue, physical discomfort, which can also affect the emotional expressions on the face. Therefore, other factors must be considered when diagnosing a person's emotional state solely based on their facial image.

The generalized diagnostic scheme can be presented as follows (Figure 1.5).

In the initial diagnosis of human EPS, verbal methods are used. One of the most common of these is psychometric testing, which allows for the objective determination of the degree of expression of a particular emotion, as well as the identification of personality traits related to the emotional sphere during patient interviews (anamnesis). One of the most widely used psychometric tests is the STAI (State-Trait Anxiety Inventory), which is used to determine the level of anxiety in a person [160, 161]. Furthermore, when conducting additional research or examinations to determine human EPS, non-verbal methods based on the analysis of physiological indicators, such as electroencephalography and electrocardiography, are also used [162, 163]. Additionally, non-verbal methods based on image analysis, particularly facial images, can be used to determine human EPS. The face is an important source of information about a person's EPS, as it can reflect emotional states and mood expressions.

Various methods are used for facial image analysis that do not require additional specialized equipment for generating input data, particularly methods in computer vision and intelligent data analysis. Machine learning algorithms can be employed for the automatic determination of EPS, which is clearly reflected on a person's face. Different training models can be used for this purpose, based on a large number of facial images showing different emotional expressions.

When selecting a method for EPS research, particularly for facial image analysis, it is essential to consider the features of the research object, such as the characteristics of the facial images, their resolution, and quality. It is also important to keep in mind that facial image analysis can be dependent on context and other factors that may influence the person's emotional state.

For example, in the work [164], computer vision methods are used for facial image analysis and EPS determination based on facial image analysis using Python libraries, DLib, and OpenCV. In the work [165], neural network models are used for the automatic detection of emotional expressions in facial images. In the work [126], an overview of deep learning-based methods is presented to address the task of identifying emotional expressions on a person's face.

The application of facial image analysis methods for studying human EPS is a promising area of research. The use of computer technologies allows for the automation of the analysis process and reduces the impact of subjective factors on the research results. However, additional studies are necessary to confirm the accuracy and reliability of using facial image analysis methods for determining human EPS.

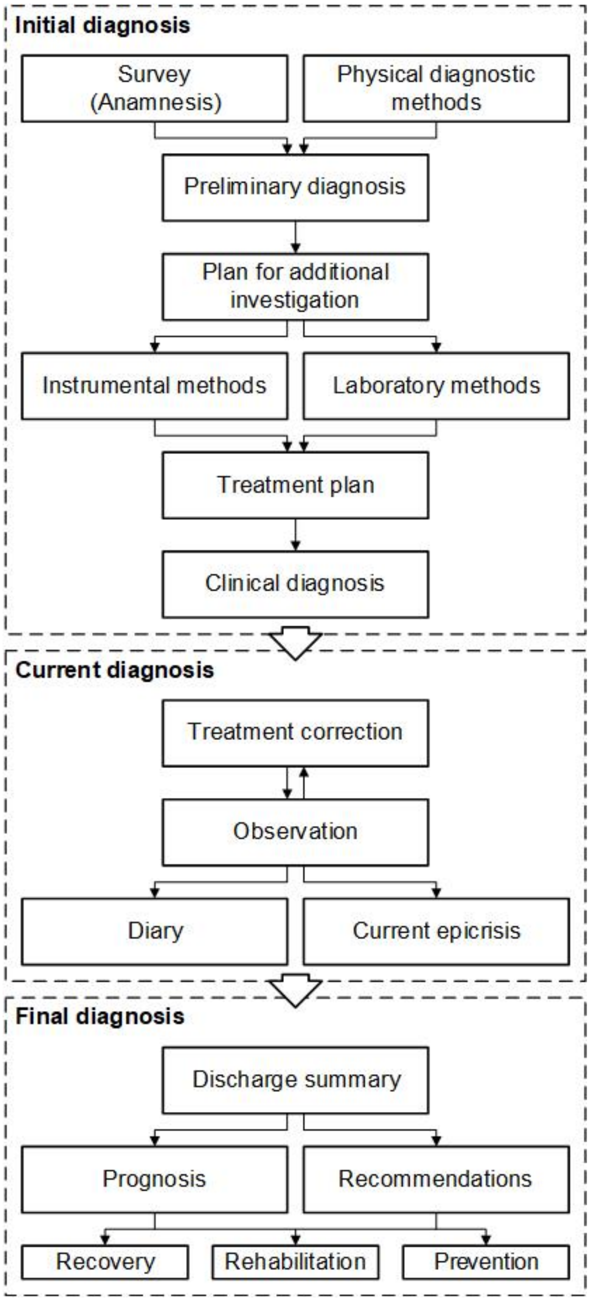

Fig. 1.5. *Generalized Diagnostic Scheme*

Overall, the choice of the method for studying human EPS should be based on a comprehensive analysis of objective criteria and the characteristics of the research object, considering the possibilities and limitations of the chosen method and adhering to ethical research principles. The use of diagnostic methods allows for identifying various mental states and emotional disorders, which can be helpful for further treatment and rehabilitation of the patient. Currently, the widespread use of human EPS diagnostics is becoming increasingly relevant, as the number of people facing various emotional and mental problems continues to grow. The mass use of EPS diagnostics can be achieved through various methods and tools. For example, modern technologies such as image analysis can help track emotional expressions on a patient's face. Additionally, computer systems can be used to analyze expressions and other signs that indicate a person's mental state. At the same time, such systems must meet a number of fundamental requirements to be effective and reliable [166, 167]. These requirements may include:

- Reliability: The system must have high reliability to ensure the stability of research results over time and under different conditions.
- Objectivity: The system must provide objective results that are independent of subjective evaluation.
- Validity: The system must measure what it claims to measure, i.e., measure what is actually happening in psychological processes.
- Normativity: The system must have standards that allow comparison of research results with those of other people.
- Wide range: The system must have a wide range of indicators that allow measurement of various aspects of a person's psyche.
- Effectiveness: The system must be effective in helping diagnose and understand a person's psychological state.
- Non-standardization: The system must be standardized and normalized to ensure the comparability of research results between different people and conditions.
- Ethicality**:** The system must adhere to ethical standards regarding the subjects being studied, ensuring data confidentiality and using data only with the consent of the individuals being researched.

Adherence to these requirements ensures high-quality psychodiagnostics and the accuracy of the obtained results, which is crucial for understanding human psychological processes and solving various problems related to the psyche.

Human EPS is characterized by a complex of emotional, cognitive, and behavioral responses that arise in reaction to various internal and external stimuli. Depending on the nature and intensity of the factors influencing psychological resilience and the individual's reactions to external stimuli, two classes of EPS are distinguished: stable and unstable.

Stable human EPS is characterized by the absence of sharp mood swings and behavioral changes. This state reflects the stability of the personality in response to various stressful situations and the ability to adapt to new conditions. Individuals with stable EPS are characterized by balance and self-control, which enables them to succeed in various areas of life. Diagnosis of stable mental states is typically carried out using psychological tests and questionnaires, which are verbal methods and allow for the identification of personality traits and characteristics. One of the most well-known tests for diagnosing personality traits is the 16PF test, developed by Raymond Cattell [168].

Unstable human EPS is characterized by sharp fluctuations in mood and behavior, and an inability to control emotions and reactions to external stimuli. This can be caused by various factors such as stress, anxiety, depression, sleep deprivation, etc. Individuals with unstable EPS often experience fatigue, helplessness, and dissatisfaction with life, which can lead to negative consequences for their health and professional development. Various methods are used for diagnosing unstable EPS, including psychological tests, verbal questionnaires, and clinical observations based on non-verbal instrumental and laboratory methods. One of the most well-known methods for diagnosing unstable mental states is the Rorschach method, developed by Hermann Rorschach. This method is based on interpreting a person's responses to different abstract images, which helps identify various aspects of their psyche, including their emotional state [169]. In addition to the Rorschach method, there are many other methods for diagnosing unstable mental states, such as depression and anxiety tests, personality structure tests, and clinical observations and interviews. An important part of diagnosing unstable mental states is differential diagnosis, which involves distinguishing one mental state from another, a task that can be quite challenging.

To differentiate between stable and unstable human EPS, it is necessary to use special tools and both verbal and non-verbal diagnostic methods, such as testing for depression, anxiety, fatigue, and other indicators of psychological state. Observing the behavior and emotional reactions of a person in various situations can also be helpful. In the process of distinguishing between stable and unstable EPS, it is important to consider the individual characteristics of each person and the context in which they are situated. For example, a slight mood fluctuation in a person with stable EPS may be considered normal, whereas the same fluctuations in someone with an unstable state may indicate serious issues.

In fact, the result of machine-based EPS evaluation allows for its effective use in clinical diagnosis, treatment planning and adjustment, the preparation of current or discharge medical summaries, as well as indirectly as part of other comprehensive and psychological assessments (such as stress resilience, self-control, anxiety, aggression, emotional intelligence, etc.). These results include:

1) Assigning EPS to either a stable or unstable class (qualitative characterization);
2) Determining the level of stability or instability (quantitative characterization).

As shown in the first section, a promising approach to improving the accuracy of human EPS diagnosis through facial image recognition is the information synthesis of the diagnostic decision support system (DSS) within the framework of IEI technology, which is based on evaluating the information capacity of the system during machine learning. Since the apex of a structured multidimensional feature vector (simply referred to as a feature vector) for the relevant recognition class defines a point in the feature space, the decision rules developed during machine learning are practically invariant to the multidimensionality of the diagnostic feature space. It is known that if a vector consisting of, for example, an incredible number of 2^{85} diagnostic features is input into a modern computer system, it is capable of processing this information [168]. Therefore, the geometric approach, in which decision rules are built based on the results of machine learning within the IEI technology framework, is the most promising for information synthesis in the DSS for diagnosing EPS through facial images and their fragments, requiring the analysis of large amounts of diagnostic data.

An important task in analyzing the research object for the information synthesis of the human EPS diagnostic system based on facial images using information-extreme machine learning is the formation of the input information description. The components of this description include:

- A dictionary of diagnostic features;
- The alphabet of recognition classes, which describe possible EPS states in humans;
- An input training matrix of the "object – property" type;
- A working training matrix, defined in the Hamming binary space.

The identification of data patterns occurs during the information-extreme machine learning process, the main result of which is the construction of highly reliable decision rules. To solve this task, it is necessary to develop hardware and software tools for designing the DSS for diagnosing human EPS, which include technical, informational, algorithmic, software, and organizational support. A key feature of the reliability testing of the learnable diagnostic DSS software is the application of functional testing, which, unlike load testing, is performed during the classification decision-making process based on feature vectors from the recognition classes alphabet. The result of functional testing is determining the corresponding level of stability or instability of the diagnosed human EPS.

Thus, the analysis of the current state and development trends of computerized diagnostic systems in medicine, as well as the intelligent technologies of their information synthesis, allows the following conclusions to be made:

1. The analysis of face recognition methods allowed for the identification of key research directions in this field and the conclusion about their effectiveness and limitations. The development of new face recognition methods, particularly using deep learning, is a promising research direction in the field of face recognition that could be applied in many areas, including security, medicine,

advertising, and entertainment. For further research, it is recommended to explore the possibility of combining face recognition methods with other emotional analysis methods.

2. Computerized diagnostic systems in medicine are becoming increasingly popular and are widely used. They help reduce errors in diagnosis and improve treatment effectiveness. Therefore, the modern trend in the development of computerized systems for diagnosing human EPS is the use of advanced intelligent information technologies for data analysis based on machine learning and pattern recognition.

3. The development of intellectual information synthesis technologies contributes to the improvement of computerized diagnostic systems. Specifically, they allow for the analysis of large data volumes and the extraction of new knowledge that can be used to enhance diagnosis and treatment. This enables the creation of more productive and efficient diagnostic and treatment systems, which reduces the risk of incorrect diagnoses and improper treatment of patients.

4. The analysis of psychodiagnostics methods allowed for the conclusion about the necessity of using a comprehensive approach to studying mental states and processes. It was found that each method has its advantages and disadvantages, so it is advisable to use them in combination with other methods, which will provide a more complete and accurate picture of human EPS. It was also discovered that a significant number of methods have an empirical basis and require further verification of their reliability and validity. To improve the accuracy of results, it is essential to carefully follow methodological recommendations and consider the individual characteristics of each research subject. Thus, the use of a comprehensive approach and adherence to methodological principles will lead to more accurate and reliable psychodiagnostics results, which is of great importance for further studying and assessing human EPS.

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