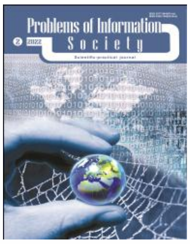

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International experience and approaches to the intellectual analysis of behavior in the e-government environment

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ABSTRACT

The role of the Internet in people's daily lives, the impact of social networks on the formation of public opinion, the spread of mobile communications, the collection of personal information in electronic information systems in the e-government environment made the problem of "behavior analysis" even more relevant. In order to improve the efficiency of the public administration process during the formation of the information society, one of the most important tasks to be performed by the government organizations is the correct assessment and prediction of citizens' behavior and making the right decisions. The main goal of the intellectual analysis of behavior is to understand the logic of the activities of individuals and social groups. This article studies the international practice in intellectual analysis of behavior, examines the methods and algorithms used in this area, and identifies problems. Proposals are developed for the effective solution of questions on the intellectual analysis of behavior in the e-government environment. The approach we propose for intellectual analysis of behavior based on textual information consists of 4 levels: 1) primary processing, 2) document description, 3) classification of a set of documents into positive and negative classes, 4) determination of accuracy and completeness characteristics in classification. The use of semantic indicators for intellectual analysis of behavior can help conduct research with greater accuracy and effectively solve behavioral prediction problems.

1. Introduction

The human factor is the basis of financial institutions and social institutions that make up the infrastructure of the state [1]. A person's behavior is a key factor influencing his/her activities, reputation, trust (in social capital) in family and society. In the effective management of e-government, studying the position of citizens in society, security and, most importantly, to provide satisfaction with the government is very significant. As citizen satisfaction depends on the work of government agencies and the organization of governance in accordance with the needs of citizens, it is necessary to study the socio-economic situation, emotional state, behavior of citizens and take appropriate measures to address their concerns. Because the application of modern ICT tools in all areas of production is not sufficient for the effective management of e-government. Here, the behavior of each citizen in the society, its importance for the country, social capital and actions must be taken into account [2].

Behavior in the social sense means a system of activities representing the application of an individual's moral principles [2]. Human behavior is determined by a person's thinking, inner judgments, personal motives, and so forth. Moreover, a person's social surroundings, different rules in society, social norms, emotional state and many other factors affect his/her behavior [3]. Richard M. Lerner, an American scientist and professor at Michigan State University, describes a human behavior as "the potential and expressed ability for physical, mental, and social activity at different stages of human life".

The ability of networks and physical systems to work synchronously, more effectively and flexibly, led to the formation of a new generation of manufacturing industry, the 4th Industrial Revolution (Industry 4.0). The 4th Industrial Revolution not only ensured the transition of states to a new stage of economic development, but also made the problem of information abundance even more relevant. Nowadays, text information and different multimedia resources in various sources (official or unofficial reports, appeals, complaints, archives of interviews, mobile communications, e-mails, state registers, social media, etc.) are collected generatingbig data. Proper structuring and analysis of this ever-increasing data is a necessary factor in studying, predicting and managing the behavior of each citizen.

The first phase of the study explores the concept of behavior analysis and determines the scope of methods of intellectual analysis of behavior through ICT. The second stage analyzes the research conducted in order to understand and predict the citizens' behavior in the e-government environment, and studies the international experience. This stage explores the methods of intellectual analysis of behavior and classifies them according to the research areas. The last stage develops proposals to increase the efficiency of behavioral analysis.

2. Intellectual analysis of behavior: essence and application areas

Although-government management is a socio-economic and technical process, the existing social relations, ethical norms and behavior in society have an impact on this process. Behavior analysis means the scientific study of behavior, the prediction and causes of changes in behavior in education, family, workplace and other areas [5-7].

The history of behavioral analysis in the fields of sociology, philosophy and psychology can be attributed back to prehistoric times. Human activity, social status, economic status and the impact of mood on behavior were always in the interest of scientists. The analysis of behavior through information technology is a new field and emerged in early 21st century [6]. Currently, the principles of behavioral analysis applying ICT tools are used in education, medicine, transport, family, banking and insurance operations, internal relations, in determining the psychological state of individuals, organizing services for children and people with disabilities, and increasing effectiveness in production [7–9].

Behaviors are classified as individual and collective. Individual behavior is demonstrated by an individual, whereas collective behavior is observed in the joint behavior of any group, collective, or community members [8]. Behaviors observed in the information society can be classified according to two different environments: individual behavior in physical life and behavior in the social environment, i.e., how to use social media resources, social relations, interests, etc. [10–12].

Various registers store information obtained from video surveillance systems, mobile phones and electronic documents. Although the capabilities of registries allow to process, summarize, and decrypt this information, they are not sufficient to address decision-making and forecasting issues. The main reason for this is the problem of "big data" and the fact that the data to be processed is unstructured and in different formats [12]. Recently, intellectual systems, big data technologies and machine learning methods are widely used in data analysis to solve these problems partially. Artificial intelligence and sentiment analysis methods predominate in this type of research. Basically the analysis of tonality in text, video and audio information is a widespread field of research to study the behavior and attitudes of citizens [11, 12].

Preliminary information on the intellectual analysis of behavior is obtained from social media resources, video surveillance cameras, as well as from different registers. Government agencies, large companies, banks and insurance systems try to estimate the citizen and determine his social credit by analyzing his/her behavior. Social credit means the assessment and classification of citizens in society according to their behavior, education, abilities, purchasing capacities, interests, trust and a number of other characteristics [13]. Social credit affects the reputation of the citizen and is necessary for the correct assessment of social processes. In the next step, some approaches to intellectualanalysis of behavior will be considered.

3. International experience in intellectual behavior analysis

Various approaches are available on the intellectual analysis of behavior, including trust and authority. These approaches range from simple statistical calculations to clustering and optimization models.

A) Intellectual analysis of behavior through video surveillance. [9] proposes an intellectual system that analyzes the driver's distracted behavior due to fatigue and insomnia in order to reduce traffic accidents. The system uses images from both a car-mounted cameras and roadside video cameras to analyze individual shots in real time. The neural network-based fatigue and insomnia detection system analyzes changes in a person's facial features. In this approach, images are pre-processed using filtering and face detection algorithms. The uncommon movements are analyzed using the Local Binary Pattern algorithm, and Max pooling is used to reduce the complexity. The sleepy state of an individual is defined using the SVM (Support Vector Machine) classifier.

The traditional video analytical methods used for intellectual analysis of behavior include, first of all, in-depth training and classification methods [10]. The in-depth training model made a major revolution in video analytics. The use of deep neural networks (Deep Neural Networks, DNNs) made it possible to develop video analysis systems imitating human behavior.In-depth training eliminates the need for human participation and experience in the technical system, and automatically learns the features required to solve the problem. This approach has led to the development and widespread use of many areas of artificial intelligence, such as machine vision.

One of the proposed models for studying egocentric activity and behavior in daily life is the model for detecting and evaluating behavioral activity [11]. This approach is based on the step-by-step processing of data collected from different sources to identify objects and events. In the first stage, the state of the object is determined using the "status-activity" association table. In the second stage, an image is obtained using a convolution neural network (CNN) and the data obtained by determining the image entropy are classified according to the subject. In the third stage, the movement data set is reclassified by the Support Vector Machine (SVM). At the end of the study, the anomalous activity in the behavior is determined by classifying the general results obtained.

International experience for the image-based anomalous behavior detection is mainly based on the rules [12]. This model identifies all functions as motion models. The system is trained according to rules to identify anomalous behavior. If the observed event does not comply with the established rules, it is registered and the analysis system is activated. The work of the system for behavior recognition is grouped into stages: data pre-processing; detection of symptoms; object tracking; determination of behavior. Here, functions are identified as movement models. The system is trained according to rules to detect an anomalous event. If the observed event does not comply with the established rules, it is registered and the analysis system is activated. The proposed approach is based on the Gaussian Mixture Model (GMM). The advantage of the rule-based model is that the relationship between anomalous events and objects can be easily determined by changing the rules.

Independent Component Analysis (ICA) has a significant role in the intellectual analysis of behavior. ICA is a statistical and computational model and restores the structure of data and reveals hidden factors out of big data. Since behavioral indicators can be obtained only by analyzing the observed data, these indicators are called free components of the observed data [14]. That is, here the intellectual analysis of behavior is based on the processing of data collected as a result of observation. This method is widely used in medicine to analyze human behavior [14, 15].

The Markov chain is widely applied in intellectual analysis of behavior. For instance, Alex Pentland, a professor at the Massachusetts Institute of Technology, and his co-author state that each individual's behavior can be accurately described as a set of dynamic models (such as Kalman filters) connected in series with the Markov chain [16]. Although it is possible to define behavior through the Hidden Markov Model (HMM), this approach is not sufficient to create an observation model or predict behavior. Therefore, researchers propose the combined use of the Kalman filter and the Markov chain to describe and classify complex behaviors based on the physical properties of an individual's movements. Simple non-trivial models for behavioral modeling include single dynamic processes. In the suggested simple dynamic model, the individual's state vector is given as follows [16]:

$$X_k=f(X_k,\ t)+p(t)$$

where, the function f models the dynamic evolution of the state vector X_k over the step k, $p(t)$denotes the noise with a known spectral density at time t. The approach predicts the situation as follows:

$$X^*_{k+1} = \hat{X}_k + f(\hat{X}_k, t),\ k = 1,2,..n$$

where k is the number of steps in the filter algorithm, and $\hat{X}_k$ is the optimal linear state. It should be noted that an individual's behavior is not as simple as a single dynamic model. The most complex model of behavior is that a person has several alternative models of movement dynamics. An individual's behavior changes at each moment, due to various situations. Therefore, it is more suitable to use the Dynamic Markov Model (DMM) to apply different models for each time period in the analysis of an individual's behavior.

Dynamic Markov models are mainly used in the analysis of data obtained from sensors and video surveillance systems to recognize behavior and predict it in seconds. In international practice, the DMM describes how a number of dynamic processes need to be managed to generate an observable signal, rather than trying to directly describe a signal about an individual's behavior. Initially, changes in the behavior of an individual observed in DMM can be identified by assessing different behavioral situations. Precise adjustment of this topology can be done empirically. For instance, obviously driver's behavior depends on the road and the rules of the road. Suppose that the driver's behavior is assessed in 4 situations: 1) the driver turns the car to the left, 2) stops the car at a traffic light, 3) the car moves on, 4) the car stops. These four situations, which describe the behavior of the driver, can be assessed using the DMM model. It should be stated that in order to describe each state, it is possible to describe its structure by grouped it into subdivisions through the DMM. As with HMM, there are three main problems with using DMM: evaluation, computation, and decoding [17].

According to the method suggested in [18], the intellectual system performs the process of detecting anomalous behavior in three stages: detection and recognition of objects; classification by body condition; detection of abnormal behavior. In order to detect objects here, the Kalman filter is used. 10 body conditions are taken into account in the classification according to body condition. However, the accuracy of the system is not so satisfactory. Thus, the system cannot distinguish some actions. For instance, the system perceives actions such as a person falling or bending as identical.

One of the behavioral detection methods is the model of automatic image and behavior study (Appearance and Motion Detection, AMD). This model reveals anomalous events by detecting the appearance and movement of motion and objects. The model uses noise-reducing autoencoders to study appearance and movement functions individually and altogether. An auto-encoder is a neural network that transfers input data to output data to reduce the amount of data or noise being analyzed [19]. Following the training, several SVMs from the same class are prepared. These SVMs predict the anomaly score of each input. Then the results are combined and an abnormal event is detected.

One of the suggested methods for studying behavior as a result of video surveillance is the model of *Feature Tracking and Image Segmentation to Comprehension Behavior (FSCB)* in real time [20]. The proposed approach focuses on the detection of behaviors based on visual signs and image segmentation. The research uses statistical analysis, background subtraction, image segmentation and classification methods. The advantage of this approach is that there is no need for training methods. The computing speed depends only on the frame rate.

Research shows that the CNN model is often used in object recognition for intellectual analysis. The in-depth learning architecture, especially the CNN model, is significant in big data analysis. The deep CNN model was first used to detect objects in 2013 [21]. Article performs object detection and localization issues. CNN is less effective in analyzing small data, but CNN will present a more accurate result if a large amount of data is used to identify, classify, and detect an object [21, 22].

The methods and algorithms proposed to study the behavior of a citizen in real time in any public place, to identify and predict the anomaly are not very accurate, and there are errors depending on the scene, the environment, the surveillance camera used. The main difficulty in research in this area is the real-time data analysis.

B) Intellectual analysis of behavior based on textual information. Intellectual analysis of text-type data is one of the most common approaches in the intellectual analysis of behavior. By analyzing documents, letters, comments, and other textual information, it is possible to make consideration about an individual's behavior, mood, and view of events. Nowadays, however, text-type information forms big data and is often collected in various sources in an unstructured manner that cannot be used without initial processing [23]. Primary processing of textual information means, first of all, tokenization, i.e., the splitting up of the sentences into separate tokens (words). Then the stop-words are cleared and stemming is performed. Clearing stop-words means the process of clearing each text from commonwords and symbols (punctuation marks, etc.). Stemming is the process of removing the suffixes of a word and finding its root.

“Text mining” technologies are widely used in the intellectual analysis of different types of documents and knowledge management. Intellectual analysis of a document (text) means the process of extracting the necessary information from large scale information. Different methods exist for processing an excessive number of documents. These include information extraction, clustering, classification, generalization, etc. [24] addresses the issue of detecting hidden social networks by clustering unstructured text-type data. The traditional “fuzzy c-means” algorithm is used to solve the problem. Fuzzy clustering allows a given set to be divided into crisp sets under certain conditions. Using this algorithm, it is possible to collect semantically relevant texts in clusters. [25] suggests a document abstracting method by clustering sentences. The analysis of textual data became more relevant due to the rapid dissemination of ideas on various topics, the expansion of social networks, which are the best means of information sharing. The research explores the methods of text-type data analysis in the social network. It is observed that the analysis of textual information helps deeper understanding of person’s attitudes, views, feelings and emotions towards other people and to predict future social behavior.The study determines the mood of the authors and their attitude to any information on the basis of sentiment analysis of comments on social networks. The main purpose of the study is to define the hidden social networks suspected of implementing an anti-government propaganda, the main actors involved in this network and their importance based on the analysis of citizens’ opinions in the e-government environment. The Pointwise Mutual Information (PMI) method is used to calculate the polarity rate of each word in a sentence.

Considering the influence of human psychology on behavior, [26] the authors try to study an individual’s behavior based on an analysis of the texts written by him/her. The aim of the research is to determine the psychological mood, to understand and predict the behavior of the individual by conducting an intellectual analysis of text-type data. The approach uses ISI Web of Science, Engineering Village Compendex, ProQuest Dissertations and Google Scholar databases as a data source. Sentiment analysis of unstructured texts on various topics is implemented by search in these databases by keywords, and the psychological state of the author is studied by classifying the texts as positive and negative.

Regarding the determination of a citizen’s behavior on the basis of the analysis of textual information, [27]presents that it is possible to assess the individual on the basis of daily correspondence, i.e., to link the textual information with social behavior. This study has two main significances. First, the textual information that people communicate with others is analyzed, focusing on the identification of the key methodological approaches to understand the author’s psychological behavior by processing the expressions used in the text. Second, “text mining”, which is used to predict behavior, identifies research shortcomings and features needed to develop analytical tools and methods.

Some researches attempt to study the interests and psychological state of users operating on virtual social networks by analyzing their behavior. Thus, grouping the information shared by network users into positive and negative classes is the most common research method[25, 28]. It is stated that all the comments made by users in this type of research can be applied to the psychological prognosis of these users.

In international practice, methods of automatic detection of emotions are widely used in the study of human behavior. For instance, [29] proposes a new method based on the *electroencephalogram* signal to classify human emotions. The signal identifies the electrical activity of the brain and provides useful information about a person’s emotional state. In the approach, using the symptom vector and the decision tree classifier, in both two-dimensional and three-dimensional models, emotional states are distinguished by factors such as tension, excitement, and dominance. [30] proposes a new approach based on the selection of local features for automatic categorization of documents. This approach collects terms with a high degree of affiliation, and an experimental comparison is made on four characteristics: “chisquare”, correlation coefficient, probability ratio, and GSS (General Social Survey) coefficient. According to the results, the suggested approach classifies the text in more effective way to determine whether it is negative or positive.

Another study suggests a socio-scopes model for analyzing human behavior and social networking based on detailed records of cell phone calls [31]. The authors make use of probability theory and statistical methods to quantify social groups, relationships, and patterns of communication, and to detect changes in human behavior. The research also proposes a new index to measure the level of interaction between the individual and each individual's data sharing partners.

In international practice and standard approaches, automatic classification of text by tonality is carried out mainly through dictionaries SentiWordNet [32] and WordNetAffect [33].

C) Intellectual analysis of behavior based on mobile communication and speech. Obviously, communication between people, a person's thought and emotional state are based on speech. It is possible to study and predict a person's behavior by determining his/her emotional state according to speech. Extensive research is conducted in this sphere by private companies, security agencies and various government agencies. Depending on the mood of the speech, the timbre, strength and other characteristics of the voice are different. Breaks, dynamics and emphasis in speech are also necessary for the study of behavior [34].

[35] defines an informative feature for each audio recording and evaluates the feature for classification efficiency. This approach is based on the importance of pre-determining certain parameters for speech analysis. These parameters include the frequency of the sound; tempo of speech (number of words expressed in a timeunit); outline of the main tone of voice; sound power assessment, etc. Generally, neural networks, systematic analysis and various classification methods are widely used in speech analysis [36, 37].

[38] proposes a new approach for speaker identification by determining the emotional tone of the speaker. The suggested approach uses a common recognition algorithm to identify emotion in speech and speech recognition [38]. The approach is based on two-stage recognition. The algorithm uses both HMM and upper segment Hidden Markov Models (SPHMM) as classifiers. The experiment examines six emotions, including neutral, angry, sad, happy, disgusted and frightened emotions. Based on speech analysis, [39] defines the accuracy of speaker identification in the unnatural environment to be lower than in the everyday human environment. Classification is performed to evaluate and predict behavior according to speech. The research uses the CNN method applying three separate speech data bases. Consequently, the CNN method surpasses other classifiers in accuracy.

Study shows that mood and emotional events are important aspects of behavior, and it is significant to consider emotional factors in the intellectual analysis of behavior (**Fig. 1**). The study also presents that in international practice, machine learning, a rule-based approach and ready-made dictionaries are widely used for intellectual analysis of behavior.

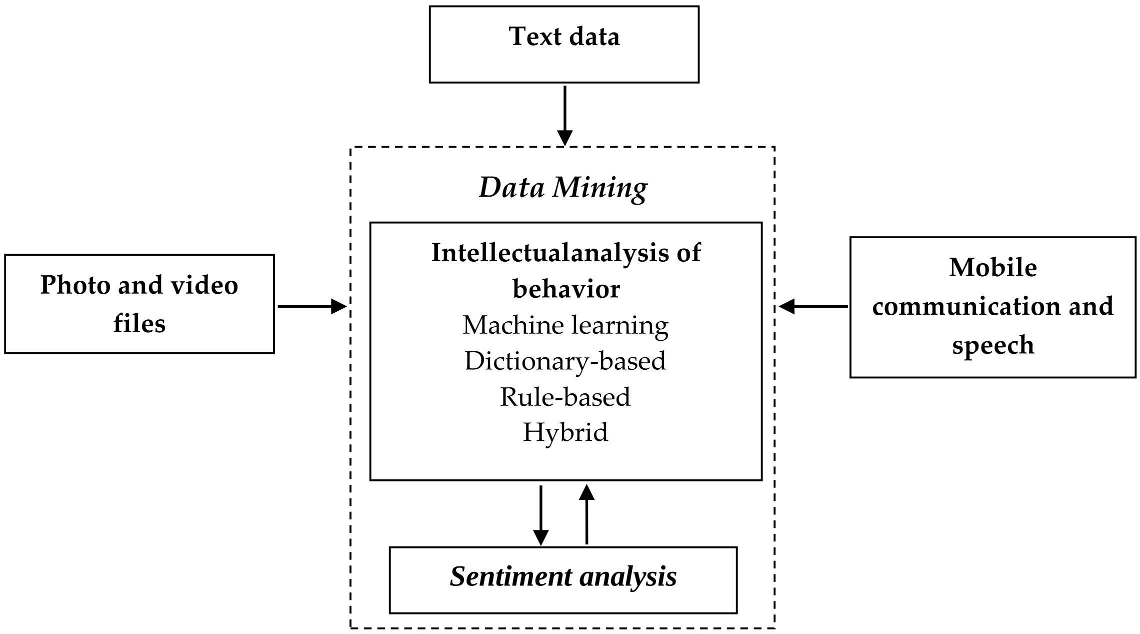

Fig. 1. General scheme of intellectual analysis of behavior based on multimedia resources

Content Analysis methods are widely applied in computer linguistics in the analysis of emotionality in the text, and in many cases, it is called Opinion Mining [40, 41]. In other words, sentiment analysis is a part of content-analysis methods and is designed to automatically determine emotionality in text and other multimedia resources.

An emotional expression indicated at the level of a communicative fragment or lexeme is called a lexical tonality or lexical sentiment. The text tonality is defined entirely by the lexical tonality of its units and the rules of their combination [42].

In most studies, intuitively, it becomes traditional to analyze a citizen's behavior by dividing it into several prototype behaviors. For instance, classifying into categories such as negative behavior, neutral behavior, and positive behavior, is useful both for solving the big data problem and for simplifying the problem. The idea is to choose a method that determines the tonality so that we can minimize the number of neutral (D^0) behaviors by correctly classifying negative (D^-) and positive (D^+) behaviors. In view of the above, the majority of all behavior sets D_i of a citizen U_i can be summarized as follows:

$$D_i = D_i^+ \cup D_i^0 \cup D_i^-, i = 1,2,\ldots,n$$

It is suitable to use the sentiment analysis method to classify a citizen's behavior as positive, negative, and neutral ones. Using this experience, we can introduce dynamic models corresponding to three types of behavior on intellectual analysis of behavior. We can classify behaviors by determining which model the behavior of any individual conforms to. An individual's behavior can be identified and understood by obtaining indicators with semantic characteristics. Metadata, including concepts, events, keywords, and categories, should be taken into account in solving such problems. These issues can help to make more efficient decisions (for example, personnel selection, proper advertising, in-depth study of the object in insurance issues, etc.) or the analysis of intelligence.

Our research suggests that the methods of classification and clustering in the intellectual analysis of behavior perform better results. It also turns out that by grouping the variables representing citizen's behavior into categories (classes), assessing the citizen's behavior as positive and negative provides a more effective solution to the problem.

The approach we propose to analyze behavior on the basis of text-type information (documents) consists of 4 levels: 1) pre-processing, 2) document description, 3) classification of a set of documents as positive and negative ones, 4) determination of accuracy and completeness characteristics in classification.

1. *Pre- processing* morphologically analyzes the words involved in the set of documents and extracts common words from the text, i.e., defines the main terms in the set of documents.

2. *Document description stage* describes each document (in this case, each document d_m of the set D_i) as a vector. The widespread Vector Space Model can be used for this. By this model, each document is displayed as a vector in m-dimensional Euclidean space. A set of documents pertaining to an arbitrary individual U_i can be indicated as follows: $D_i = (d_1, d_2, \ldots, d_{m_i})$, where m_i is the total number of documents.

3. *In the stage of sentiment analysis of documents, the negative and positive indicators are used as an evaluation factor*. The dictionary of subjectivity is indicated here, that is the difference between weak and strong words expressing any idea is calculated. Weak words are rated 2 (positive) or -2 (negative). Strong words are rated 4 (positive) or -4 (negative). The approach uses the Senti-WordNet lexicon database. The Senti-WordNet dictionary was created using WordNet and contains a "sunset" structure. It should be stated that each document has a set of sunsets:

$$w_i \in synset(w_i),\ i = 1,2,\ldots,n$$

Based on this experience, the tonality of each word is determined based on the words assessment.

4. *Precision and Recall characteristics of data classification* are quality indicators applied to data obtained from a collection or any database [43]. Accuracy can also be viewed as the ratio of the number of true positive results to the total number of elements listed as referring to a positive class. In this research, the accuracy is the number of correctly stated as a result of the classification of documents related to the citizen, whether they refer to the positive or negative classes. Accuracy and completeness are not so necessary indicators when used separately. Basically, the value of one indicator is determined by comparing the value of another indicator.

4. Conclusion

Research indicated that there are various international practices and approaches for identifying and predicting an individual's behavior by analyzing text, video, and audio information. The 4th Industrial Revolution, the application of artificial intelligence to social, economic and many other fields, the "big data" and the "Internet of Things" led to the further complication and improvement of methods of analyzing people's moods and behavior. In the research, we got acquainted with various international practices and approaches to the intellectual analysis of behavior, identified areas of research, and the main problems complicating this.

International experience indicated that video and photography, textual information, and speech are widely used in the intellectual analysis of an individual's behavior. The traditional video analytical methods used for intellectual analysis of behavior included, first of all, in-depth training and classification methods. The in-depth training model made a major breakthrough in video analytics. The use of *Deep Neural Networks (DNNs)* eliminated the need for human intervention and experience in a technical system by enabling the development of video analysis systems imitating the human behavior, they also automatically learned the features required to solve any problem. This approach led to the development and widespread use of many spheres of artificial intelligence, such as machine vision.

"Text mining", fuzzy sets and clustering dominate in the analysis of text-type data. Research also showed that machine learning methods were widely used in the intellectual analysis of an individual's behavior, depending on the data source. In particular, *K-Nearest Neighbors, Naive Bayes classifiers, Decision Tree, Artificial Neural Networks,* and *Support Vector Machine* methods are widely applied. Neural networks, probability theory, and statistical methods are widely applied in the intellectual analysis of behavior based on mobile communication and speech.

Although the classification of emotions using artificial intelligence is a new field in the intellectual analysis of behavior, it is already widely used. Many approaches to the study of human behavior based on the analysis of unstructured textual information are available. However, there is still a need for new research for a broader understanding of the expansion of the information society, the role of people in the 4th industrial revolution, and how important they are for the country.

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