Network Model of Multiagent Communication of Traffic Inspection for Supervision and Control of Passenger Transportation in Road and City Traffic

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Abstract - **As a rule, the supervision and control of the transportation of persons in different types of traffic is the responsibility of the Traffic Inspection of the state inspectorates of individual countries. This paper investigates the intelligent supervision and control of the transportation of persons in road and city traffic managed by the Traffic Inspection in the geo-space of the Republic of Srpska (RS). The aim of the research is to create a multiagent communication (MAC) network model of an ensemble of intelligent interactive teams of human agents (HA), software agents (SA) and cyber-physical agents (CPA) located in six distributed nodes of a star network topology. All nodes of this topology represent Intelligent communication agents, and a special team of intelligent management agents for Inspection Affairs is located in the sixth node of the MAC network model. In the proposed model, the communication platform for MAC is supported by process-adaptable applications of machine learning methods, and the ability of agents to learn from experience and predict based on digital data processing. The main goal of MAC model is optimization of solutions for timely planning, reliable functioning, continuous monitoring, preventive supervision and effective management of Traffic Inspection tasks in uncertain situations contexts.**

Keywords - multiagent communication, traffic inspection, agent, transport of persons, prediction, classification, categorization, situational contexts

I. Introduction

Logical and structural, traffic and transport systems are engineering systems whose structuring and behavior are inevitably influenced by innovative-technological, legal-regulatory, organizational-cultural, energy-ecological, social-contextual and other environmental factors. They are holonic structures characterized by the great complexity of the constellation of relations and relationships between numerous components of the system. The complexity of the configuration of states in the entire system, or some of its components as modules function is investigated in real situations. In the structure of the traffic system module of road and urban passenger transport, a special functional component is the *traffic inspection*. This is the subject of research in this paper, where the geo-space of the Republic of Srpska (RS), Bosnia and Herzegovina (BiH) was chosen as a case study. In this geo-space the system and process structuring and functioning of traffic is carried out according to technical-technological standards, norms, algorithms and protocols. This takes place in the organizational-management and social-contextual domains on the basis of prescribed legal norms and rules. Legal norms and consequent rules are prescribed by a set of Republican and state laws, international regulations, decrees, specifications and specialized functional and non-functional procedures. Traffic inspection works are planned, implemented, monitored and controlled according to the defined roles of intelligent agents in simple, complicated and complex situational contexts of the traffic system.

The hypothetical premise of this research is that the content-functional, technological-process and relational-contextual structure of traffic inspection works can function more accurately, precisely and reliably according to the network model of multiagent communication (MAC). The concept of the model is based on the interactive roles of human (HA), software (SA) and cyber-physical (CPA) communication agents and management agents. Agents function on knowledge and learning through the execution of tasks of supervision and control over objects of traffic flows and transport processes in unstable situational contexts. In the focus of communication agents are problems and solutions from the domain of safety of traffic participants, reliability of exploitation of mobile objects and stable infrastructure objects. Also, an important goal of MAC is information security of structured data and messages that are transmitted, exchanged and shared between singular agents, groups, teams and ensembles in the network architecture.

Intelligent management agents monitor, evaluate and control value attributes of structural dimensions of functional, equivalent and management processes, implementation of strategy theory in activities, legal behavior of HA in singular and plural roles of traffic inspection. At the same time, points of interest are the functional and non-functional specifications of operational technologies, software applications and cyber-physical modules of learning and management in unstable contexts of road traffic flows. The interaction field of meaningful, dynamic, proactive, irreversible, interactive and contextual multimodal communication behavior of management agents in the ensemble is expanded by cooperation with non-inspection bodies and organizations. Their aim (goal) is solving specific tasks of prediction, classification, categorization and evaluation of inspection supervision and control works. Based on these conceptual settings, the proposal of the MAC network model of a real ensemble of interactive groups and teams HA, SA and CPA, which are located in six spatially distributed nodes of the star network topology, was created in the paper. The model is goal-oriented towards clearly defined functional tasks, stable problems and finding solutions through improving the way of working and decision-making in the work of the Traffic Inspection. The action platform of the MAC network model is supported by process-adaptive applications of machine learning methods and the ability of agents to learn from experience and make predictions based on digital data processing. Section 6 of this paper presents the results of training and testing of a classification model for solving one of the tasks within the intelligent and legal behavior of human agents in the singular and plural roles of the Traffic Inspection. The relevance of the model was tested in a case study in a selected geo-space of traffic area with the goal that the created solutions can have universal applicability.

II. Review of Relevant Published Research

So far, numerous studies have been published related to the application of the MAC model in the field of road and city traffic with different target orientations. In paper [1], an original model of the Next Road Rerouting (NRR) vehicle routing system based on the communication of intelligent agents was proposed. The goal is to assist drivers, based on the cost function, the driver's destination and local conditions, in finding the optimal route in order to avoid unexpected traffic jams. In [2], the authors presented a new adaptive multiagent system for road traffic management based on the ant colony algorithm, which is characterized by adaptability and the short time required to calculate new vehicle movement routes. The subject of research in [3] is a model for multiagent traffic signal control based on the decentralized and scalable Multi-Agent Reinforcement Learning (MARL) method. Considering the existence of a very large number of intersections in an urban traffic environment, the authors in [4] use Independent Reinforcement Learning (IRL) to solve the problem of cooperative traffic control. The aim of the research presented in [5] is to develop a multiagent traffic simulation methodology in order to evaluate potential road safety improvements using new technologies. In paper [6], the traffic signal control optimization problem is formulated as a distributed constraint optimization problem. Multiple agents are used to control road traffic based on traffic density at adjacent intersections. The study presented in [7] deals with the application of multi-agent learning algorithms with support for cooperative traffic signal control. A method based on Multi-agent Deep Deterministic Policy Gradient (MADDPG) was proposed in order to reduce the average waiting time of vehicles. Similar research was published in [8] where a traffic optimization system based on agent technology and fuzzy logic was presented.

III. The Roles of Intelligent Agents in the Multiagent Communication Model

In this paper, agents are "explicitly observed situated or positioned entities in the road and city traffic system that communicate" interactively in the contexts of HA, SA and CPA role performers in traffic inspection activities. The roles of groups, teams and ensembles of intelligent communication agents are oriented towards solving the tasks of monitoring and controlling actions, activities, events and processes in the domain of consistent application of traffic normative-legal regulations, representation of technical standards in traffic-infrastructure facilities, traffic-safe exploitation of dynamic facilities in public transport of people by buses, taxis and vehicles of rent-a-car agencies. In addition, agent roles in the MAC network model digitally treat data on the reliable operation of vehicle technical inspection stations, the safe operation of fuel filling stations and other external road and city traffic infrastructure facilities. In reality, communication is inseparable from some mode of information processing. The analogy established by the research between the computer and human way of information processing and the compatibility of physical data flows with the operations of software applications in cyber-physical systems enabled the development of multi-agent communication in the changing and adaptable situational contexts of road and city traffic and transport. Based on this, for the competent role-playing of the traffic inspection, the levels of knowledge and competence of the HA, the validity of the SA program and the functional ability of the CPA are important. Knowledge capacity and learning of all agents is a common characteristic on which the goal and methodology of creating a network model MAC in traffic inspection work is based.

Human agents (HA) - it is known that the human body functions as a neurophysiological system on three interactive communication platforms - cognitive, behavioral and conative. The human cognitive system has a powerful memory architecture whose components are: sensory register (SR) - closely connected with the modular sensory system; short-term, conscious, working memory (SM) and long-term memory (LM) in which experience and knowledge about phenomena, events and other knowledge are stored. Knowledge can be episodic (about specific events in spatio-temporal contexts) and semantic (abstracted from the spatio-temporal context). Semantic knowledge is declarative (know that) - general knowledge about the characteristics of a phenomenon or event and procedural (know how) - knowledge about procedures and actions which achieve certain goals. In the description of these components of the cognitive system, several communication dimensions are used, namely: source of information (speech, image, sound, computer data), capacity, function, length of retention of information, form in which information is stored, ways of which information is lost. On the behavioral platform HA communications can function at the level of data. In simple situational contexts - at the level of information, and in complicated situational contexts - at the level of acquired knowledge and applied knowledge. But in complex situational contexts, their communication must function at the level of intelligence and wisdom or the level of the total capacity of the repertoire with all the mentioned types of cognitive continuum. On the conative platform, HAs function depending on the type, complexity and specificity of the tasks they perform in the traffic inspection business. Therefore, in HA management, the most important role is business process management (BPM). BMP is seen as a set of business process-oriented management approaches (BPO) instead of a classic functional organizational structure.

Software agents (SA) - although there are a large number of definitions of SA, papers [9,10] state that SA represents a software component capable of exchanging knowledge and information. Also, in the literature there are a large number of properties that can be attributed to software agents. In the paper [11], encapsulation, autonomy, interaction, persistence, activity and goal-oriented behavior are listed as strong properties, while mobility, truthfulness, benevolence and rationality are highlighted as additional weak properties. In the paper [12], the properties listed are autonomy, cooperation and learning of SA, on the basis of which their further classification can be made. Autonomy means the ability of agents to act without human intervention based on their internal states and goals. Proactivity is a key element of their autonomy and defines the ability to "take the initiative" [12]. Cooperation or collaboration with other agents is the ability to interact with other agents or humans using a language. Software agents learn while reacting and/or interacting with their environment, and learning is precisely one of the key features of every intelligent being [12]. Therefore, SA can be defined as an autonomous software entity located in an environment where it can proactively or reactively monitor and react to changes. This reaction is also possible through communication with other agents, in order to achieve a certain goal on behalf of the user or other agents [9,13,14]. Since SA autonomous units are capable of running on distributed computers, communication between agents is Machine-to-Machine (M2M) communication. Intelligent SAs are usually modeled and programmed with agent-oriented programming languages based on the principles of modal Belief-Desire-Intention (BDI) logic [15].

Cyber-physical agents (CPA) - represent the integration of components of the biological, physical and virtual world. Within the MAC model, they perform their role by acquiring data on physical variables using sensors, automatically controlling elements of the physical world using actuators, and promptly providing information for users and other agents. The virtual or cyber component of CPA is based on embedded computers that monitor and control physical processes in a network where many things happen in parallel, usually with feedback loops [16,17]. This means that physical processes also affect computer processes, which are defined by sequential steps. The feedback loop between physical and computational processes includes sensors, actuators, physical dynamics, calculations, software failures and network problems, communication delays. Thus, hardware elements - sensors, microcontrollers and actuators, as part of CPA function integrally with cyber elements such as computer algorithms for data processing, for monitoring and controlling physical processes, for making decisions, for managing storage locations and for data analytics [16,17].

The learning module and the decision-making module are integral parts of the CPA architecture. They play a very important role in the analysis and modeling of a large amount of collected data in physical streams that are fed into virtual sensor-network applications. The best solution lies in adaptive models based on artificial intelligence that have the ability to learn. Therefore, the most common techniques and algorithms implemented by the learning module are based on machine learning. Thus, virtual (software) sensors can also perform learning and decision-making functions based on various data obtained using physical sensors [17].

IV. Topology and Interactions in the Model of Multiagent Communication

In the proposed real network model of Traffic Inspection MAC, the agent teams are connected in a star network topology, as shown in Fig. 1. Each communication agent team has a point-to-point connection with the central management team. Intelligent management agents in the sixth-central team meaningfully, dynamically, proactively, irreversibly and interactively collaborate with all other agents of the ensemble. The management team node, which has the role of a server, controls all other network nodes in the roles of clients and is responsible for routing all data and information in the network. Management agents pursue goals respecting the environment and their defined space of action. Also, they create operational goals for the benefit of HA or other management agents with a certain degree of autonomy. Management agents proactively manage goals, take responsibility, make decisions, and create a model of their environment.

Communication agents distributed in six regional teams (Fig.1) enable agents to communicate with each other and generate the correct flow of relevant information at the exit point of the inspection process (Fig. 1(a)). They must possess the ability to reason in order to understand any information or actions in the inspection process. This also refers to the goals of management agents in generating the performance of traffic inspection works.

Within individual teams, as already mentioned, there are SA, CPA and HA that are connected in a Full Mesh topology, where each agent is connected to all other agents by direct links (Fig. 1(b)). In this way, the redundancy of the connection is increased, as well as the speed of data transmission and the robustness of the network. In this peer-to-peer network team model, each agent performs the role of server and client. The displayed network topology of six distributed teams of agents corresponds to the territorial organization of the observed space, which consists of six regions according to the

Spatial Plan until 2025. Therefore, each of the six teams belongs to one region: Team 1 - Prijedor, Team 2 - Doboj, Team 3 - Bijeljina, Team 4 - East Sarajevo, Team 5 - Trebinje and Team 6 - Banja Luka. The headquarters of the *Republic traffic inspection* is located in Banja Luka. That is why this city was chosen as the central node or the sixth team of agents, while each region includes several local self-government units.

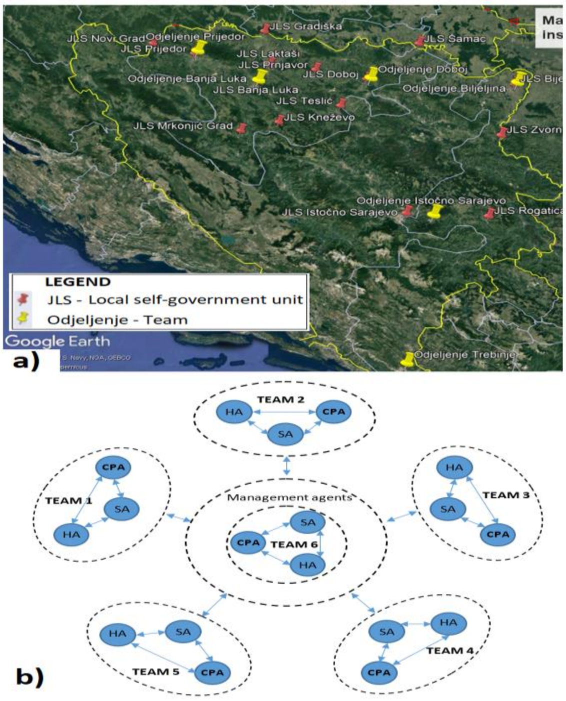

Figure 1. Communication agents distributed in six regional teams (RS, BiH): (a) Map of agents of the RS Traffic Inspection; (b) Network topology of the Traffic Inspection MAC model

Fig. 2 shows the interactions in the MAC Traffic Inspection model that imply on request or periodic exchange of data and information between agents in a team and between ensemble teams. Given that it was previously stated in section 3 that CPA consist of physical and virtual components, each of them has its own roles and tasks within the agent team and ensemble of the proposed MAC model. The physical component uses sensors to acquire data from the environment where objects and inspection control and monitoring processes are located (e.g. vehicles, drivers, roads, documentation, etc.).

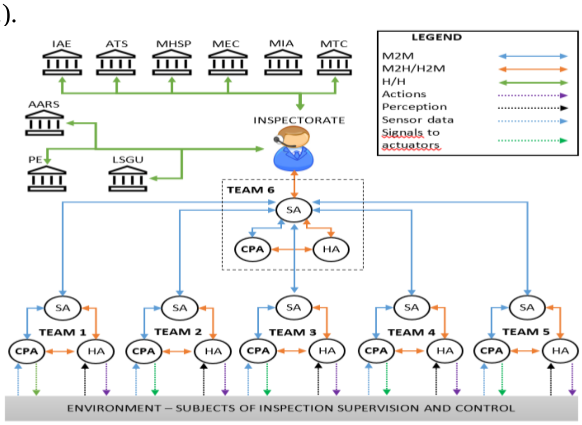

Figure 2. Interactions in the proposed MAC model

The virtual or cyber component of the CPA processes this data in the learning module and the decision module, and forwards the information to actuators or HA that act on the physical world (eg. by alerting inspectors or the police). In addition, CPA may forward information to SA and/or HA. HA or inspectors in the field receive data from the environment by perception, and after processing, perform actions on objects of control and supervision or forward data and information to SA and CPA. SA provide support to HA and CPA in data processing with machine learning methods and applications, which is shown by the results of the classification predictive model in Section 6 on the example of one of the Traffic Inspection's monitoring and control tasks.

Each agent communicates with all other agents from the team. Thus, the communication between HA and CPA, and between HA and SA is Human-to-Machine/Machine-to-Human (H2M/M2H), and between CPA and SA is M2M. The management team of the agent ensemble processes data from all teams and, if necessary, returns results, orders and tasks to individual teams. Important information is forwarded to the Chief Republic Inspector of the Traffic Inspection by H2M/M2H communication so that he has an insight into the work of the ensemble of agent teams. Furthermore, it is possible to direct them to the Ministry of Transport and Communications (MTC), the Ministry of Internal Affairs (MIA), the Ministry of Education and Culture (MEC), the Ministry of Health and Social Protection (MHSP), the Agency for Traffic Safety (ATS), the Institute for Adult Education (IAE), Automobile Association of RS (AARS), public enterprises (PE), entrusted management of the road network, bodies of local self-government units (LSGU). This way of forwarding data and information, from collection from the environment, through an ensemble of agents, all the way to institutions at the top of the jurisdiction, can be characterized as bottom-up. In addition, tasks, requests and inquiries can be sent from the top and passed down to agents in individual teams acting on the environment, which corresponds to a top-down flow of data and information.

This paper examines the intelligent and legal behavior of HA - traffic inspectors, expressed through numerical scores on a scale from 1 to 5 as an example of one of the tasks of supervision and control of the Traffic Inspectorate. Machine learning models for the classification of agents according to scores, the results of which are given in section 6, have been implemented in SA and allow the management team to evaluate the work of inspectors in the field, based on the input data obtained by contextual sensors or by other HA that have the role of control and supervision.

V. Machine Learning Models for Solving Inspection Monitoring and Control Tasks

In the proposed model, the MAC platform is supported by machine learning techniques, the most common of which are: 1) Artificial Neural Networks (ANN); 2) Decision Trees (Classification And Regression Trees - CART); 3) Support Vector Machines (SVM) [18]; and 4) k-Nearest Neighbors (k-NN).

In general, machine learning models usually represent very good solutions for prediction and classification problems in various fields. But, some research suggests that it is often necessary and desirable to transform the machine learning problem into a problem of cooperation between agents. In that way, the problem is broken down into several smaller problems that are solved by individual agents, thereby reducing its complexity and enabling the system to adapt to the evolution of individuals [18]. Our paper, proposed the MAC model consists of an ensemble of agents that can solve problems of control and supervision of the transportation of people in road and city traffic. That is a distributed manner using the Ensemble Learning method based on the idea of combining multiple individual machine learning models, commonly referred to as "weak learners". It can result in a model with better predictive performance than any single model. There are two main approaches to ensemble learning [18]: Bagging and Boosting [19]. Considering that one of the key steps for defining a model or an ensemble of ML models is the selection of independent/input and dependent/output variables. Table 1 shows input and output variables by individual models for solving the problem of monitoring and control in the tasks of traffic inspection.

TABLE I. INPUT AND OUTPUT VARIABLES OF THE MODEL FOR SOLVING TRAFFIC INSPECTION SUPERVISION AND CONTROL TASKS

Supervision and control tasks	Input variables	Output variables
1. Consistent application of traffic regulations	Type of regulation; Geographical location; Subject of control.	Number of offences
2. Representation of technical standards in traffic infrastructure facilities	Municipality/city; Control object: 1)Physically stable and some mobile objects of traffic and transport; 2)Legal-regulatory, energy-economic, security-protective and ecologically-sustainable facilities; Organization in charge of maintenance; Age of the object; Period of the year.	Safety assessment of facilities; Control result.
3. Traffic-safe exploitation of dynamic facilities in public transport of people by buses, taxis and vehicles of rent-a-car agencies	Number of regular controls of technical correctness; The number of extraordinary inspections of technical correctness; Prices of services; Regularity of departures in public transport;	Level of satisfaction of users of transport services [20]
4. Intelligent and legal behavior of human agents	Level of government; Competences; Role in the team; Location where it operates; Level of functional knowledge.	Agent grades
5. Functional implementation of operational software and cyber-physical technologies in the context of traffic flow security	Annual investments; The level of use of conventional business technologies; The level of use of Information Technologies (IT); Level of use of communication technologies (CT); Use of personal networks; The level of use of information and communication technologies (ICT); The level of use of software applications in CPA interactions.	Achieved results in terms of safety; Number of traffic accidents.

In accordance with the fourth task of supervision and control given in Table 1, the following are observed as input or independent variables of the machine learning model for the classification of HA according to grade: *Level of government (Level)*, which can be municipal or republican; *Competence*, expressed through attributes such as: experienced, communicative, meticulous, strict...; *Team role*, which can be: republican inspector, chief republican inspector, regional coordinator, city inspector or municipal inspector; *The location where it operates (Location)*, which means the city/municipality in the RS; *Level of functional knowledge*, which can be: data, information, knowledge, applied knowledge, intelligence, wisdom, capacity for knowledge sharing and exchange at complexity situations. The agent's grades, which can be a discrete value in the interval from 1 (unsatisfactory) to 5 (excellent), is viewed as the dependent or output variable.

VI. A MACHINE LEARNING MODEL FOR THE CLASSIFICATION OF AGENTS BY GRADES

This section presents the results of training and testing of machine learning models for solving one of the tasks within the intelligent and legal behavior of HA in singular and plural roles of traffic inspection. The goal is to classify the agents according to their ratings depending on the previously mentioned input/independent variables. The creation of the classification model was performed in the IBM SPSS Modeler software environment, whose main purpose is to work with predictive and classification models. The collected data for model training and testing are structured into 48 input/output vectors, 70% of which belong to the training set and 30% to the model testing set. Using the automatic classification method using the Auto Classifier option, models based on SVM, k-NN and CART techniques with default parameters were examined. After training and testing, SPSS Modeler ranked the mentioned models according to the overall classification accuracy, and the results are shown in Table 2.

TABLE II. RANKING OF THE TESTED MODELS FOR THE CLASSIFICATION OF AGENTS ACCORDING TO GRADES

Tested model	Overall classification accuracy
1. CART	84.615%
2. k-NN	69.231%
3. SVM	69.231%

As it can be seen from the results given in Table 2, the best classification performance is shown by the model based on CART machine learning technique with 84.615% accuracy of classified vectors. Models based on k-NN and SVM have equal classification accuracy values of 69.231%. As an significant result of the training and testing of the mentioned models using the Auto Classifier method, Fig. 3 shows the importance of the influence of each of the five independent variables (Predictor importance) on the classification results. As can be seen from the picture, the level of functional knowledge is the most influential variable on the classification results. But the level of action of the agents (municipal or republican) is the variable with the least influence on the classification performance of the model.

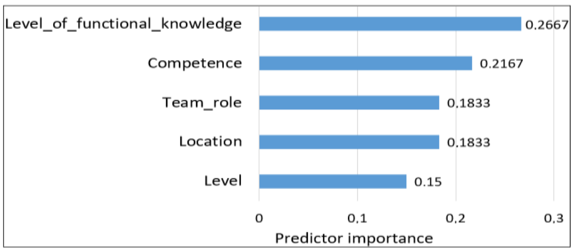

Figure 3. The importance of the influence of each of the five independent variables on the classification results

Fig. 4 shows the classification results for the best created model - CART according to Table 2. The x-axis of the diagram shows the grades of the agents from the data set for testing, while the y-axis shows the number of tested observations. It can be concluded that grades 2 (satisfactory) are correctly classified in all 6 observations, grades 3 (good) are correctly classified in 5 observations, and grades 4 (very good) are misclassified as well as grade 3 in two observations from the test set.

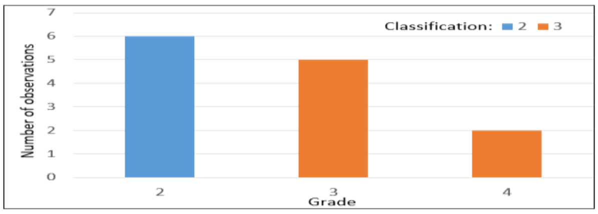

Figure 4. Agent classification results according to grades for the CART model

VII. Conclusion

The research in this paper is focused on the modeling of multiagent communication in the work of the Traffic Inspection which supervises and controls road and city traffic. The MAC model is presented in relational, descriptive, analytical, visual and classification modes based on the use of features of interactive HA, SA and CPA. Even though the relevance of the model was tested in selected geo-space of RS traffic area the aim of the created solution can have universal applicability. The MAC is presented in a star network topology with six distributed nodes according to the geo-locations shown on the map where intelligent communication agents are located. The sixth node also having intelligent management agents. A special diagram of interactions shows the possible state of functioning of the MAC.

In order to verify the functionality of the created MAC, machine learning models were specially created for the classification of HA categorical variables based on the collected grades of the agents. Data on selected independent and dependent categorical work variables in control and monitoring processes and tasks are structured in 48 input/output vectors, of which 70% of the volume is in the training set, and 30% in the model testing set. Using the automatic classification method by the Auto Classifier option, models based on SVM, k-NN and CART techniques with default parameters were examined. After training and testing, SPSS Modeler ranked the mentioned models according to the overall accuracy of the classification. The results indicate that the conceptual analysis, subject and methodology of the research justified the status of a scientific-innovative choice of the type of problem in the field of strengthening traffic safety. Actually that is a new topic of research in traffic and transport engineering systems. The main drawback and limitation of the paper is that the proposed model solves only one problem within the framework of traffic inspection supervision and control. Therefore, future research directions are oriented towards the modeling of other inspection and control tasks, as well as the application of the Ensemble Learning method to improve the accuracy performance of the model classification using the Boosting approach.

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