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APPLICATION OF ARTIFICIAL INTELLIGENCE TO CONTROL AND PREDICT THE QUALITY OF ASPHALT CONCRETE COATING

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ABSTRACT: The article is devoted to the problems of controlling and predicting the quality of asphalt concrete pavement at the laying stage using artificial intelligence methods. An intelligent system is proposed that uses a neural network model to analyze key process parameters-temperature, humidity, compaction pressure, and placement speed-to identify potentially defective areas. The developed system allows you to identify areas with a risk of under compaction even during laying, which allows the operator to timely adjust the technological parameters of the process. As a result, the implemented system achieved a prediction accuracy of 96%, which significantly improves the efficiency of real-time coating.

KEY WORDS: artificial intelligence, machine learning, asphalt pavement, quality prediction, thermography, compaction, defects, road construction.

1 INTRODUCTION

Artificial intelligence (AI) is one of the key areas of modern engineering technologies development. The use of AI in industry, transport, and construction makes it possible to automatically analyze large amounts of data, create forecasting models, and make decisions in real time [1–4]. In road construction, such technologies allow us to move from traditional post-construction control to systems that predict possible quality deviations during the construction process [5].

The results of recent scientific research confirm the possibility of using machine learning methods and deep neural networks to determine the relationships between

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technological parameters of the laying process and the performance properties of asphalt concrete. It is shown in [6, 7] that the use of combined (ensemble) models, recurrent neural networks and methods for classifying large data sets increases the accuracy of predicting the evenness, strength and durability of the road layer. The most interesting systems are those that process data from temperature, humidity, and compaction pressure sensors in real time [8, 9].

In parallel, artificial intelligence methods are being developed to assess the building materials condition. Deep learning is an effective means of detecting surface defects and predicting changes in the structure of materials from images or thermographic data [10,11]. The research results in this area create a theoretical and practical basis for using similar approaches in asphalt pavement quality control.

The development of artificial intelligence technologies in combination with sensor systems and big data analysis methods is forming a new direction - intelligent monitoring of road construction processes. This increases the accuracy of control, reduces the influence of the human factor and creates conditions for automatic adjustment of asphalt concrete laying parameters [3, 4, 7, 10, 11].

2 Analysis of Recent Research and Publications

The study [12] addressed the accuracy problem of existing pavement condition indices, in particular the Pavement Condition Index (PCI), which are based mainly on visual observations and subjective assessment of inspectors. The authors note that such methods do not take into account the complex relationships between various defects, traffic loads, road age, and climatic conditions, which leads to inaccurate assessment results. The aim of their work was to create a new intelligent approach to assessing the technical condition of asphalt concrete pavement using deep learning methods, which would eliminate the traditional indices disadvantages.

A large data sample was formed, including more than 15 thousand records with characteristics of defects, layer thickness, traffic intensity, climatic indicators, and age of road sections to achieve this aim. Based on this data, the authors created a deep neural network model (Deep Feed-Forward Network) capable of independently detecting patterns between parameters and calculating a new generalized state index. To verify the results, the neural network was compared with classic machine learning algorithms such as decision trees, support vector machines, and random forests.

The results obtained showed that the proposed model demonstrated an accuracy of the pavement predicting condition at the level of 92–93%, while traditional methods did not exceed 85%. The proposed index turned out to be more resistant to noisy data and better reflected the influence of several factors simultaneously, such as the interdependence between coating age, defect type, and climatic conditions. However, the authors also noted certain limitations of their work. Training the model requires

a large amount of high-quality labeled data, which limits its application in regions with insufficient field measurements. In addition, the model is focused mainly on assessing of the pavement condition after the operation start, while its integration into control systems during laying still requires further research.

In the article [13], the authors analyze the automatic detection problem of defects on the various materials surfaces using deep neural networks, in particular convolutional neural networks (CNN). They emphasize that traditional visual inspection methods have low efficiency, require significant human resources, and cannot quickly cover large volumes of production or infrastructure. To address this issue, they conducted a systematic literature review according to the PRISMA methodology, initially identifying 253 publications, of which 59 met the sampling criteria.

The study classified the works according to the following parameters: surface type (metal, building materials, ceramics, wood, others), task type (classification, object detection, segmentation), network type used, methods applied (e.g. transfer learning, data augmentation), and data sources (cameras, datasets) were also considered. In particular, it was found that metal surfaces predominate in such studies (62.71% of cases), that operators most often solve the classification problem (49.15%), and that transfer learning methods were used in 83.05% of studies, and data augmentation in 59.32%.

The results show most studies successfully apply CNN architectures, but the authors also highlight some limitations. The majority of the work is carried out on small data sets with limited coverage of different materials or environmental conditions. There is no agreed methodology for evaluating the model effectiveness, which makes it difficult to compare results. A significant part of the research focuses on only one type of problem (e.g., classification) without integration with other quality control aspects.

The authors also note a number of shortcomings in the research conducted. The results obtained may be less relevant for road surfaces, as most studies focus on industrial production surfaces (metal, ceramics, etc.) rather than asphalt concrete or roads. Also, the defecting processes in road materials may have a different nature than those studied in the review. In addition, most models are not tested in real-time conditions or directly during the installation or operation process.

In the study [14], the authors considered the problem of time-consuming and expensive physical inspection of road surfaces, which often does not provide coverage of a large network in a timely manner. They set out to create a deep learning model to estimate the road surface condition from satellite images to provide a scalable, less costly approach. To do this, they collected more than 3,000 satellite images of pavement sections with corresponding data on their condition from the Texas Department of Transportation (TxDOT) database. Several pre-trained neural networks (e.g.

VGG19, ResNet50, InceptionV3, DenseNet121) and an ensemble voting method were used to improve accuracy. The results showed an accuracy of over 90% (or ˜93% according to some models) in classifying the condition of the pavement into the categories “very good”, “good”, “average”, “bad”, “very bad”. Among the limitations, the authors realize that the satellite resolution (ground sample distance) is low and does not allow for the small defect detection (such as cracks or ruts) at an early stage. Also, the system is more suitable for network-level inspection than for detailed local one.

The authors [15] pay attention to the problem of asphalt concrete pavement destruction and the appearance of a such type defect as “raveling” - disintegration of the upper layer of asphalt concrete pavement under the traffic and weather conditions influence. The paper indicates that traditional methods of defects visual inspection do not provide sufficient accuracy or efficiency for maintenance planning.

Researchers collected images of the asphalt pavement surface using a portable 3D laser scanner (LS-40) to solve this problem. Next, they performed image preprocessing (histogram alignment, rotation, and mirroring to increase data versatility). This allowed them to obtain clear structural data of the surface. Then they implemented several deep learning models, including transfer learning using pretrained models: ResNet-18, DenseNet, VGG16, Inception, EfficientNet. The model was trained to classify between a normal surface and a surface with a raveling-type defect.

The results showed that the EfficientNet model showed the best performance, with an accuracy of about 0.96, precision ≈ 0.95, recall ≈ 0.96, F1-score ≈ 0.96. The Inception model also performed well, with an accuracy rate of ≈ 0.95. The authors note the model has real potential for practical application, in particular in road infrastructure control and management systems.

However, the work has certain limitations. The data sample is limited to images obtained on a single university campus (or local area), which may reduce the generalizability of the model to other pavement types, different climatic conditions, or structures. The model works with a binary classification (defect/normal surface) rather than assessing the degree of the defect or predicting the further “raveling” development. The system is not yet integrated into the asphalt concrete laying process or real-time process control, it is rather intended for surface inspection after laying and operation.

In work [16], the authors considered the problem of insufficient accuracy and scale of assessing the structural condition of asphalt concrete pavement, in particular at the network level of road sections. They point out traditional methods are based on sample measurements using devices such as Traffic Speed Deflectometer (TSD), but this data has a high cost of collection and does not cover large networks effectively.

To solve the above problem, researchers collected data from 950 miles

($\approx 1,530$ km) of roads in the state of South Carolina (USA). They used TSD measurements and information on average annual daily traffic (AADT), truck percentage, and speed limit. This data was used as the basis for a classification model that assumes two structural road conditions - "poor" or "non-poor". The authors used machine learning algorithms - XGBoost and Random Forest - in comparison with logistic regression. The results showed that XGBoost outperformed Random Forest and logistic regression. Specifically, the accuracy of the XGBoost model was ˜12% higher than logistic regression and ˜4% higher than Random Forest. Also, analysis of the feature importance revealed that AADT has the greatest impact on the forecast. The percentage of freight transport also has some impact, while speed limits have almost no impact.

However, the authors noted some features of their research. Only three explanatory variables were used (AADT, truck percentage, speed limit), which limits the model completeness. The data was from a single state and may not be representative of other climatic or structural conditions. The model was of a classification type and did not have a regression estimate of the damage level or a prediction of the defect development over time.

In [17], the problem of road damage automatic detection and classification based on images obtained in several countries where conventional approaches do not generalize well to other regions is considered. The authors set out to test whether it is possible to build deep learning models that will work for different countries and different shooting conditions, as well as to create a large generalized dataset for training such models. To do this, they collected and combined several sets of images from roads in India, Japan, and the Czech Republic, and prepared a scaled and annotated dataset (RDD2020/RDD-2022) with different types of damage: transverse cracks, longitudinal cracks, alligator cracks, potholes, etc. They then applied a transfer learning approach where they used pre-trained networks as a base and trained them on their images. The authors experimented with several data augmentation architectures and strategies, worked out criteria for cross-country markup agreement, and cross-validated models within and outside of mini-samples of each country.

The results showed that transfer learning models, with proper pre-processing of data, are capable of achieving high accuracy in detecting and classifying the road damages within the countries in which they were trained, and with a minor loss of accuracy can be transferred to other countries through additional training or adaptation. The combination of efforts to create a large multinational dataset and recommendations for markup standardization has become an important achievement for researchers. They have released the RDD2020/RDD-2022 set of different damage types as a resource for the community to facilitate reproducibility of experiments and comparison of algorithms.

At the same time, the paper identifies limitations. Differences in imaging conditions (camera resolution, viewing angle, lighting) and in pavement design lead to significant variability, which is why locally trained models lose some of their accuracy when directly applied to other regions. The work focuses on the detection and classification of visible defects in images, but does not provide a solution for quality control during the laying process itself (e.g., based on temperature or sealing sensors). Operational integration of models into organizational workflows (issues of data transfer, long-term model support, format standardization) requires additional research and practical tests in real conditions.

The authors of the work [18] considered the problem of operational quality control of hot asphalt concrete mixture compaction directly during laying. They emphasize traditional control methods, such as core sampling or the use of nuclear density meters, provide accepted accuracy, but do not allow for real-time evaluation, nor do they provide the opportunity to adjust technological parameters in a timely manner. The main goal of the research was to create a model based on an artificial neural network (ANN) capable of determining the level of compaction of the asphalt concrete layer during the rolling process, based on data from the roller's onboard sensors.

To achieve this goal, an experimental data collection system was developed. It includes temperature, vibration, frequency, and acceleration sensors mounted on a vibrating roller. Data were collected during the compaction of different types of hot mix asphalt concrete in the field. After initial signal processing and noise filtering, the authors formed a training sample in which the target variable was the layer density obtained from laboratory control results. A multilayer perceptron with three hidden layers and a nonlinear ReLU activation function was used to build the model. The training process was carried out using the backpropagation error method, and optimization was carried out using the Adam algorithm.

The results showed the artificial neural network model successfully reproduces the relationship between the roller vibration characteristics, the mixture temperature, and the achieved layer density. The average deviation of the predicted density from the actual laboratory data did not exceed 1.8%, indicating high accuracy. The authors also demonstrated that using the model allows for the identification of "risk zones" of undercompaction in real time and visualization of them on a map of the paving area. This allows the operator to timely adjust the speed, amplitude or number of passes of the roller.

The authors noted several limitations despite the positive results. The proposed model was trained on data obtained for only two types of asphalt concrete mixtures, so its application to other materials requires recalibration. The sensor system required stable wireless communication, which can be a problem in an active construction site. The model only estimates density, but does not take into account factors such as air humidity, substrate condition, or temperature field heterogeneity, which also

affect the final coating quality. The authors noted further research should be aimed at expanding the set of sensory parameters and integrating the model into a complete automated installation quality control system.

The study [19] examines the problem of the increasing control accuracy of the asphalt concrete pavement compaction during laying. The authors note existing Intelligent Compaction (IC) systems mostly use a limited number of parameters – such as temperature or number of roller passes, and do not take into account the complex interaction between equipment specifications, mix properties and external conditions. This leads to significant variation in actual coating density even with identical process settings. The aim of the study was to create an integrated machine learning-based model for predicting asphalt concrete density in real time, taking into account multidimensional sensor data.

To build the model, a comprehensive data collection system was developed directly from the roller, equipped with a GPS module, inertial measurement units (IMU), temperature sensors, vibration sensors, and acceleration sensors. Data was collected during the compaction process of hot asphalt concrete mix on real road sites, and measurements of actual density were performed by selecting cores for further model validation in parallel. The received signals were synchronized by coordinates, cleaned of noise, and normalized. The gradient boosting model (XGBoost) was chosen as the prediction algorithm, which was compared with the multilayer perceptron (ANN) and random forests (RF).

Experimental results showed that the XGBoost model provides the highest accuracy in density prediction with a coefficient of determination RI = 0.94, mean absolute error MAE = 0.018, and root mean square error RMSE = 0.026. It was found that the most significant factors affecting the quality of compaction are the temperature of the mixture, the amplitude of the roller oscillations, the speed of its movement, and the number of passes. Based on these results, the authors created an interactive compaction map that visualizes the density at each point in the pavement, allowing the operator to identify areas of undercompaction in real time and adjust equipment operating parameters.

The authors noted several limitations of the proposed approach despite its high accuracy. The model was tested only on sections with flat road geometry, so its generalization to complex topographic conditions (slopes, turns) requires additional training. The experiments were conducted for a limited range of laying temperatures (145–165 °C), so the effectiveness of the method at lower temperatures remains uncertain. Stable system operation requires high accuracy of GPS synchronization and reliable data transmission, which can be difficult in field conditions. The authors conclude that further development of the model should include the use of deep learning methods and an increase in the number of sensory parameters to move from estimation to active compaction management.

Thus, the literature review indicates the significant effectiveness of artificial intelligence algorithms for the analysis and prediction of road surface quality. However, most of the work focuses on post-operational analysis. Instead, operational control and preventive intervention in the technological process of paving requires further study of the AI use directly in the process of paving asphalt concrete. The authors focused their attention on solving this issue.

3 Research Implementation

Unlike most of the considered systems, focused on analyzing the condition of the coating after its installation, the proposed system operates directly during the installation process. The difference from classic IC systems is the use of artificial intelligence for simultaneous prediction of density as a quantitative indicator (regression) and classification of areas by defect risk level, with the integration of new features T_delta and HV.

3.1 Device structure

The device part of the asphalt concrete pavement quality control and prediction system consists of the sensors complex set located on paving equipment and rollers, a data collection and transmission unit, a signal processing module, and a central computing node. The main task of the device complex is the continuous collection of parameters that characterize the conditions and quality of compaction. These include mix temperature, air temperature, humidity, compaction pressure, roller speed, number of passes, and indirect indicators of pavement density.

Vibration sensors built into the roller design record the drum's vibrations during operation. Analysis of the amplitude, frequency, and shape of oscillations allows us to evaluate the change in layer stiffness during the compaction process. Accelerometer data is synchronized with GPS coordinates, which ensures spatial reference of each measurement. Temperature sensors installed in the paving area record the temperature of the asphalt concrete mixture and the surface. Humidity and compaction pressure sensors provide additional information about process conditions. All sensor signals are sent to the microcontroller, where the initial processing of the measurement information (filtering and averaging) takes place. Then the data is transmitted to a central server via a wireless communication channel.

The collected parameters are stored in a database, where samples are formed for training and operating the artificial intelligence model. A calibration stage is provided to ensure the reliability of control results. Sensor readings are compared with laboratory-determined density values of samples taken from the same sections of road. This allows us to build a correct relationship between the dynamic characteristics of vibrations and the actual values of the material density.

3.2 PREDICTION OF POTENTIAL DEFECTS

Two classes of road surface were identified within the framework of the study: "quality surface" (has a density of at least 2.2 g/cm^3) and "defective surface" (has a density of less than 2.2 g/cm^3). Defects are considered areas with insufficient compaction, local temperature deviations of more than ± 10°C from the optimum, and increased humidity, which reduces the strength of the material. The characteristics of the classes and the limits of their permissible values are given in Table 1.

The study is limited to a small number of sensors installed on the stacking equipment, which reduces the set of input data. The network training time is less than 50 epochs, using an early stopping mechanism to avoid overtraining. This also limits the depth of the research. A machine learning model was proposed that can predict the presence of potential defects based on technological parameters. This will al-

Table 1. Class characteristics and limits of their permissible values

No.	Feature (input param.)	Marking	Unit	Accept. range	Impact on coating quality
1	Mixture temperature during laying	T_a	°C	145–165	Too low temperature → poor adhesion of grains; too high → overheating and destruction of bitumen
2	Air temperature	T_p	°C	10–35	At low temperatures, cooling is too rapid, making compaction difficult
3	Air humidity	H	%	$\leq$ 3–4	Increased humidity leads to foaming of bitumen and deterioration of adhesion
4	Roller compaction pressure	P	MPa	0.8–1.4	Too little pressure → under-compaction; too much → cracks and deformations
5	Roller speed	V	km/h	3–6	If the speed is exceeded, the compaction becomes uneven.
6	Number of roller passes	N	times	4–8	Reducing the number of passes → low density; excessive number → destruction of the structure
7	Coating density	ρ	g/cm^3	$\geq$ 2.20	The main quality criterion; below the threshold – defective coating
8	Layer thickness	h	cm	4–8	With a small thickness – rapid cooling; with excessive thickness – uneven compaction

low solving the problem of operational quality control of asphalt concrete pavement during the laying process. The input data were ambient temperature (T_a), hopper temperature (T_b), paving temperature (T_p), humidity (H), compaction pressure (P), and paver speed (V). New features were also included in the model – temperature deviation from the optimum (T_δ) and the integral effect of humidity and velocity (HV), which improved the model's sensitivity to complex technological conditions.

Determining the density of asphalt concrete pavement during laying is carried out mainly by indirect methods using sensor systems integrated into road machinery. The most common solution is to use vibration sensors mounted on rollers. These sensors record the acceleration and amplitude-frequency characteristics of the drum vibrations during compaction, which vary depending on the stiffness and density of the layer. The received signals are processed using algorithms that generate relative density indicators, in particular Compaction Meter Value (CMV) or Machine Drive Power (MDP). These parameters have a high correlation with actual laboratory measurements after appropriate calibration. To clarify the structure of the layer, ground penetrating radar (GPR) systems can be additionally used, which determine the dielectric properties of the material and indirectly assess the density and uniformity of the coating. In laboratory or control measurements, nuclear density meters are used, which provide the highest accuracy. However, they are not suitable for continuous monitoring at the facility due to radiation safety restrictions. Safe field density measurements can be achieved using non-nuclear density meters based on the principle of electromagnetic scattering, although their accuracy is somewhat lower.

Modern Intelligent Compaction systems combine data from vibration sensors, GPS positioning, temperature sensors and roller pass counters. This combination allows us to form a spatial map of compaction and predict density in real time with an accuracy of 2–4%. The artificial intelligence module processes this data, identifies areas at risk of undercompaction, and can generate recommendations or automatic commands to adjust process parameters. Thus, the assessment of coating density is implemented as a result of a comprehensive analysis of sensor signals, rather than as a direct physical measurement, which provides continuous quality control in real time.

This study logically continues the previously developed by the authors [20] closed-loop control system for the technological process of asphalt concrete laying, which provides adaptive regulation of compaction parameters. The addition proposed in this work in the form of intelligent prediction of pavement quality allows you to expand the functionality of the system and move to the stage of preventive intervention based on real-time sensor data. The intelligent prediction of pavement quality proposed in this work allows expanding the functionality of the system and moving to the stage of preventive intervention based on real-time sensor data.

3.3 Artificial intelligence module and its functioning

The artificial intelligence software module is designed to process sensor data and predict the density of the asphalt concrete layer in real time. The main data type used to train the model is the density of the material, determined by a laboratory method or a high-precision field densitometer. The input to the model is a feature vector formed from the parameters that have the greatest impact on compaction. Among them are the amplitude-frequency characteristics of the vibration signal, the temperature of the mixture, the speed of the roller, the number of passes, and the compaction pressure.

The compaction process can be modeled by a neural network or an ensemble regression model pre-trained on a large number of measurements. At the prediction stage, the system calculates the current density value ρ and compares it with the normative threshold ρ_n. When the predicted density is less than the standard, the system records the area as potentially defective and sends a message to the operator with a recommendation for re-compaction. The model can track changes in parameters as the roller passes, which allows it to detect areas with anomalous deviations in sensor signals and predict undercompaction before it actually occurs.

The efficiency of the module is evaluated by the average absolute error and the coefficient of determination between the predicted and actual density values. The implementation of the system makes it possible to generate a map of the spatial distribution of compaction in real time, which reflects the quality of paving over the entire area of the roadbed. This provides the ability to adaptively control process parameters, minimize the risk of defect formation, and increase the stability of road surface quality.

To generate a training set of 1000 examples, a simplified empirical-analytical compaction model was applied, which describes the change in asphalt concrete mix density as a function of placement temperature and moisture content:

$$\rho = \rho_{\max}\left(1 - \alpha\left(T_p - T_{opt}\right)^2 - \beta\frac{H}{100}\right), \tag{1}$$

where ρ is the current density, T_p is the laying temperature, $_{opt}$ is the optimal compaction temperature, H is the relative humidity, and α and β are empirical coefficients.

This approximation approach is consistent with experimental observations on the temperature effect on density [21] and the role of contact pressure and temperature in the compaction process [22]. The influence of moisture and its negative effect on the mixture adhesion and the properties of the coating have been proven in works devoted to moisture effects in mixtures [23].

Table 2 presents the configuration and hyperparameters of the MLP neural network model used in this work.

Table 2. Configuration and hyperparameters of the MLP neural network model

Layer	Type	Neurons	Activation	Dropout
Input	Dense	8	ReLU	—
Hidden 1	Dense	64	ReLU	0.3
Hidden 2	Dense	32	ReLU	0.2
Output	Dense	1	Sigmoid/Linear	—

The architecture has an Adam optimizer (lr $= 0.001$), a binary_crossentropy loss function for classification and MSE for regression, a batch size of 16/32, a maximum of 100 epochs with EarlyStopping (patience $= 10$) to prevent retrain. Training sample — 640 examples (64%), validation — 160 (16%), test — 200 (20%). Cross-validation was not used because the model was tested on an independent test sample with EarlyStopping. The training took place in Python using the TensorFlow/Keras library.

The intelligent system for monitoring and predicting the quality of asphalt concrete compaction implements an algorithm (Fig. 1), which is based on the sequential execution of four stages: collection, processing, analysis, and decision-making.

In the first stage, the system accumulates data from sensors (temperature, humidity, pressure, speed) in real time. The second stage includes noise filtering and data scaling using StandardScaler to equalize feature weights. The third stage — Feature Engineering — involves calculating the derived parameters (T_δ and HV), which allows the model to better take into account nonlinear physical dependencies. The generated vector is fed to the input of a neural network (MLP), which performs a regression density prediction and binary classification of the area in parallel. The final stage is to compare the result with the regulatory threshold ($\rho \geq 2.2$ g/cm^3). The operator then receives a recommendation for an additional roller pass, if necessary.

The training sample was formed based on synthetically generated data (1000 examples) using a verified empirical-analytical compaction model (formula 1). The model parameters ($\alpha = 0.005$, $\beta = 0.02$, $\rho_{\max} = 2.4$ g/cm^3, $T_{opt} = 135$°C) were determined based on field measurement data presented in [21, 22]. Each example contains 8 input parameters (T_a, T_b, T_p, H, V, P, T_δ, HV) and the density value ρ or a binary class label (the target). The distribution of density values in the sample: from 1.6 to 2.4 g/cm^3, where 72% of the examples belong to the "good compaction" class ($\rho \geq 2.2$ g/cm^3) and 28% to the "defect" class. The data are synthetic, and further validation on real field measurements is a necessary step before industrial implementation.

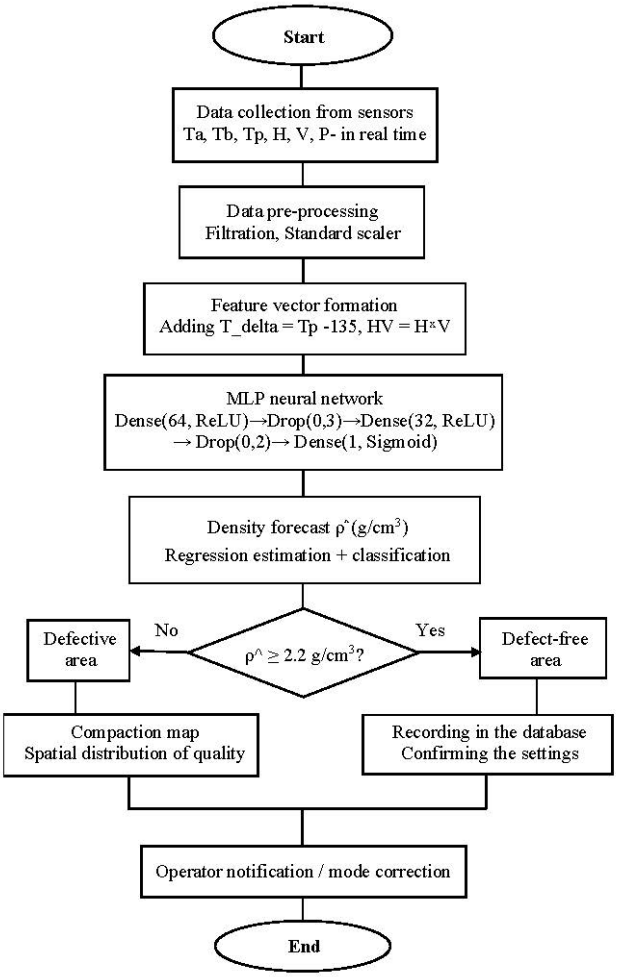

Figure 1. The algorithm block diagram of the intelligent system for monitoring and predicting the quality of asphalt concrete compaction.

4 Modeling of the Predicting Process of the Asphalt Concrete Layer Density

The quality of the coating was chosen as the main variable (0 – defective, 1 – good quality), determined by the density threshold ≥ 2.2 g/cm^3. Training was conducted using a three-layer neural network MLP, dropout to avoid overtraining, and an early stopping mechanism. As a result, the model achieved an accuracy of 96%, and the mean square error was 0.0242 g/cm^3, which indicates high classification efficiency.

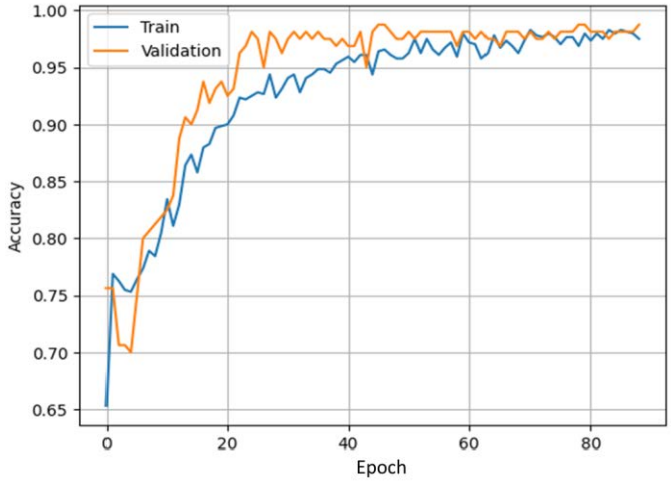

Figure 2. Graph of model accuracy dependence on training time.

As can be seen from Fig. 2, the training accuracy gradually increased, and the validation accuracy stabilized after approximately 30 epochs, confirming the effectiveness of the chosen architecture and hyperparameters. Thanks to the EarlyStopping mechanism, the process stopped automatically, which avoided overtraining and ensured a minimal gap between training and validation accuracy.

A detailed analysis of the classifier's performance is presented in the error matrix (Fig. 3). The model demonstrated high ability to identify both classes: 142 defec-

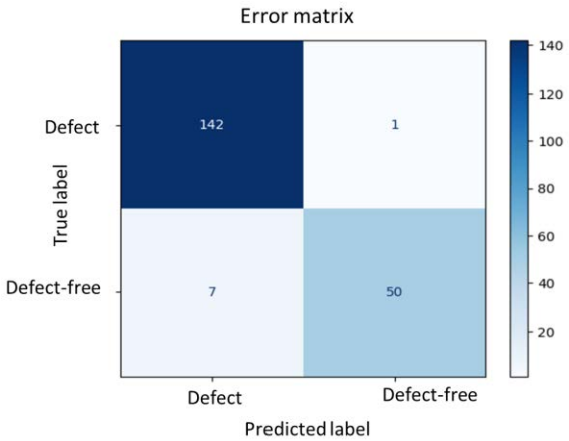

Figure 3. Classifier error matrix.

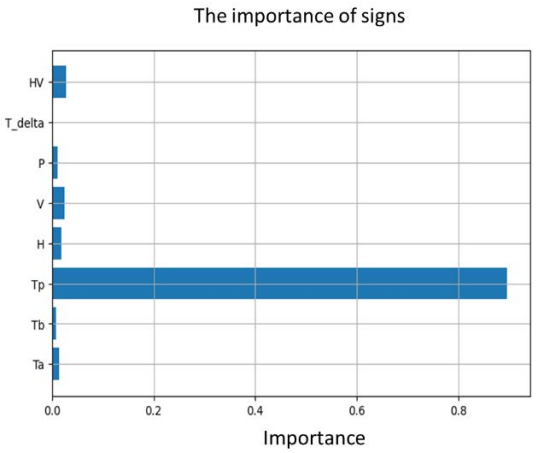

Figure 4. Feature importance diagram of the XGBoost model.

tive areas and 50 good ones were correctly identified. Only 7 false positives were recorded, which in real conditions would only result in a minor waste of time for additional compaction. The most important indicator is the presence of only one false negative result. In road control systems, this type of error is critical, since missing a defective section leads to premature road destruction, while false triggering carries only minimal economic risks.

The XGBoost model was used to determine the impact of each parameter on the model quality. Fig. 4 shows the importance of features according to the XGBoost model. The greatest influence is exerted by the laying temperature (T_p) and humidity (H), which is consistent with the physical laws of the compaction process. When the temperature of the mixture differs from the optimum (135°C) its viscosity changes non-linearly. This makes compaction either impossible due to stiffness or unstable due to excessive fluidity. Humidity, in turn, hinders adhesion and creates pore pressure, which is the main factor in the occurrence of swelling and delamination of the coating [23]. Compaction pressure (P) has a medium influence, while ambient temperature (T_a) is the least significant. This confirms that the critical parameters for the formation of a high-quality layer are temperature and humidity conditions.

To quantitatively assess the effectiveness of the model, a comparison was made of the predicting results the density of asphalt concrete pavement obtained using an MLP-type neural network and traditional linear regression (Table 3). The analysis showed that the artificial intelligence model significantly outperforms the classical approach in all major metrics. For linear regression, the mean absolute error (MAE) was 0.9284 g/cm^3, the root means square error (RMSE) was 1.1517 g/cm^3, and the

coefficient of determination RI = 0.7001, indicating limited accuracy in describing nonlinear relationships between compaction process parameters. In the case of the neural network (MLP), the average absolute error decreased to 0.2663 g/cm^3, RMSE to 0.3378 g/cm^3, and the coefficient of determination increased to RI = 0.9742. The obtained errors are considered acceptable for the operational control stage, since they allow for confident differentiation of high-quality areas from areas with critical undercompaction, where the density falls below 2.2 g/cm^3.

Table 3. Comparison of actual and predicted values of asphalt concrete pavement density

No No	Laying temperature T_p (°C)	Humidity H (%)	Compaction pressure P (MPa)	Actual density ρ (g/cm^3)	Model prediction (MLP) (g/cm^3)	Error (g/cm^3)
1	132.67	65.07	0.486	2.304	1.893	+0.411
2	136.25	27.81	0.491	2.368	2.094	+0.274
3	138.53	68.09	0.799	2.218	1.970	+0.248
4	139.69	20.04	0.607	2.127	2.052	+0.074
5	127.89	69.02	0.795	1.760	1.730	+0.031

This indicates the high accuracy of the model's prediction and its ability to correctly reflect the complex relationships between mix temperature, air humidity, compaction pressure, and actual pavement density. Thus, the use of a neural network provides an improvement in forecast accuracy by almost four times compared to traditional methods, which confirms the feasibility of using artificial intelligence in road construction quality control and forecasting systems.

As can be seen from the table, the predicted values obtained using the artificial intelligence model practically coincide with the actual results of laboratory measurements. The average absolute error is about 0.2–0.3 g/cm^3, which corresponds to an accuracy of 90–95%. This confirms the model's ability to adequately demonstrate the dependencies between temperature, humidity, and force parameters of the compaction process. Figure 5 demonstrates the approximation of the predicted density to the actual measurements. In the graph, the X-axis corresponds to the actual density, and the Y-axis corresponds to the predicted density. The dotted diagonal line represents the zone of perfect fit ($y = x$). The minimal scatter of points around this line and the high coefficient of determination (R2 $= 0.9742$) confirm that the developed neural network model is capable of adequately describing complex nonlinear compaction processes and can be used in automated road works control systems.

The high accuracy of predicting material density indicates the possibility of using the model as a basis for developing adaptive algorithms for regulating compaction quality in real time. This ensures the stability of the technological process and increases the durability of the asphalt concrete pavement.

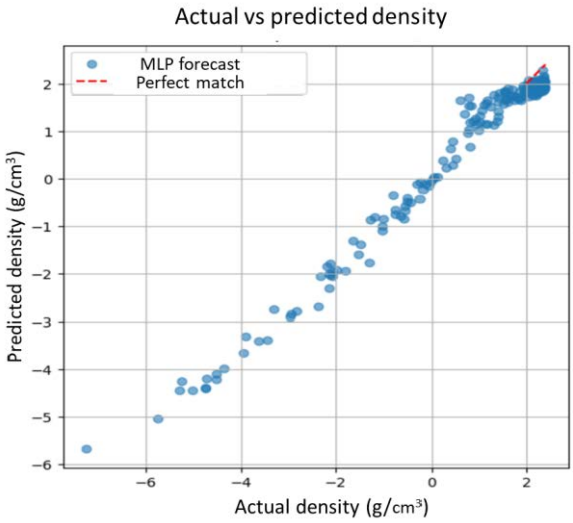

Figure 5. Model-predicted and actual road surface density.

5 Conclusions

The work developed an intelligent system for monitoring and predicting the quality of asphalt concrete pavement. The system combines sensor monitoring of technological parameters with an artificial intelligence module to estimate the density of the road surface material in real time. The proposed hardware architecture provides continuous data collection on temperature, humidity, compaction pressure, roller speed, and number of passes. The collected data forms the basis for an analytical model for roadway quality predicting.

The effectiveness of the prediction model was tested using an MLP-type neural network and traditional linear regression. A comparative analysis of the forecasting results showed that the artificial intelligence model significantly outperforms the classical approach in all key metrics. The artificial intelligence model correctly describes the nonlinear relationships between technological parameters and actual pavement density, providing an increase in forecast accuracy by almost four times compared to traditional methods. Further development of the system involves the data integration from real construction sites to validate the model in conditions of variability in asphalt concrete mix compositions and dynamic measuring equipment errors.

The developed system allows us to identify areas with a risk of under-compaction even during laying, which allows the operator to timely adjust the technological parameters of the process. The results obtained confirm the possibility of integrating the model into modern Intelligent Compaction systems to increase the stability of

the compaction process, reduce the likelihood of hidden defects, and increase the durability of the roadbed.

Further research should be directed at expanding the set of sensor data (geo-radar, infrared, non-nuclear density gauges), as well as at developing deep recurrent models capable of taking into account the temporal dynamics of compaction. This will ensure the transition from intelligent control to fully automated management of the asphalt paving process.

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