UDC 621.382:004.8
DOI https://doi.org/10.32782/2663-5941/2025.2.2/21

Momot A. S.
National Technical University of Ukraine
"Igor Sikorsky Kyiv Polytechnic Institute"

Nakonechnyi M. V.
National Technical University of Ukraine
"Igor Sikorsky Kyiv Polytechnic Institute"

Galagan R. M.
National Technical University of Ukraine
"Igor Sikorsky Kyiv Polytechnic Institute"

Muraviov O. V.
National Technical University of Ukraine
"Igor Sikorsky Kyiv Polytechnic Institute"

AUTOMATED MATERIAL CLASSIFICATION BASED ON TEMPERATURE PROFILES

This article presents a method for automated classification of materials based on the analysis of their temperature profiles. The use of laser thermography in combination with deep learning algorithms allows contactless material type recognition with high Accuracy. This is especially relevant for robotic systems that perform manipulation operations, automated quality control, and technical inspection without physical contact with the object.

A review of previous studies has shown that existing methods of material classification have certain limitations. Visual methods can be unreliable due to the dependence on lighting conditions and the similarity of the appearance of different materials. Contact methods provide high Accuracy, but they are challenging to implement and require physical interaction, which is not always appropriate in robotics. Therefore, the thermographic approach is promising, as it determines the type of material by its response to heating and cooling.

This paper describes an experimental system that uses a laser beam to heat the surface of an object, after which a thermal imager records the temperature change over time. The resulting temperature profiles are analysed using machine learning methods. The process of heat transfer for four types of materials (wood, plastic, steel, and aluminum) was simulated in COMSOL Multiphysics, which allowed us to form a training dataset.

Four neural network architectures were tested for temperature profile classification: Feedforward, LSTM, Bi-LSTM, and 1D-Convolutional. The Feedforward network demonstrated the best results, which achieved a correct answer rate of 76.6 %, although 1D-Convolutional showed better classification of certain materials. It was found that the temperature profiles of some materials have significant similarities, which complicates the classification, so further research should be aimed at expanding the training data set and optimising the model architecture.

The proposed approach has a wide range of applications in industry and robotics, requiring rapid identification of materials without physical contact. An automated system for classifying materials based on temperature profiles can increase the efficiency of technological processes, improve production safety, and expand the capabilities of autonomous robotic systems.

Key words: *material classification, laser thermography, machine learning, neural networks.*

Formulation of the problem. One of the key challenges in modern robotics is to ensure the reliable interaction of robotic systems with various objects without prior knowledge of their physical properties. Automated material type detection is critical for adaptive manipulators, autonomous maintenance systems, and robotic platforms operating in uncertain environments. For example, robotic grippers need to adjust their grip force depending on the object's material, and automated quality control systems need to assess the material of products without physical contact. Traditional methods of material recognition, such as visual or acoustic, may not be reliable enough due to dependence on lighting conditions, contamination, or similarity of appearance of different materials.

In a standard manipulation task, a robot must develop a grasping algorithm based on the physical properties of an object. Before making any physical contact with an object, it is important to determine the appropriate gripping forces for successful interaction. If the force applied is insufficient, the object may slip, while too much force may cause damage. One of the constant difficulties that arise from the lack of data on the types of materials in the environment is the lack of information on the weight and strength of unknown objects without physical contact. Thus, an urgent task is to find a method that will most effectively determine the type of material in an automated mode.

Consequently, there is a need for non-contact automated measurement of the physical properties of surrounding objects to improve the quality of robotic operations. The main difficulty lies in the fact that the surfaces of different materials may have similar textures, or, conversely, the same material may have different surfaces due to different manufacturing and processing methods. This study presents a promising approach that combines laser thermography and deep learning to implement an automated method for classifying materials by type.

Analysis of recent research and publications. Important information about the material properties can be obtained through direct physical contact between the measuring device and the object under test. This approach uses various diagnostic features of the object that occur during contact with it to recognise materials. These can include vibrations, contact forces, and thermal interactions.

Study [1] presents a haptic research method for recognising the material of an object's surface using a specially designed finger. Touch sensors provide diverse and accurate data on material characteristics and properties. However, the size and complexity of the designs, limitations on non-contact measurements, and high development costs hinder the development of a mobile and straightforward contact device.

In a study [2], researchers developed a method for determining the surface friction coefficient in various environments to optimize the performance of a bipedal robot in motion planning tasks. Although physical contact with an object allows for high Accuracy in determining the types of materials, the high cost and complexity of the design make it difficult to use this method and create an effective mobile device. Therefore, using material classification methods that do not require physical contact with the object and are easy to implement looks promising. One such method is infrared thermography [3].

Most of the existing research in this area is aimed at analysing thermograms of surfaces made of various materials. Infrared images are more informative than similar images in the visible spectrum [4]. This allows for automated classification of materials with more excellent reliability. The authors of [5] argue that typical algorithms use color and texture information for classification, but there are problems due to different lighting conditions and a variety of colors in the same class of materials. At the same time, the results show that the proposed thermal method allows for better classification results than conventional visual features of color and texture.

The approach described above is often used in machine vision systems [6]. In modern thermography, artificial intelligence methods are used to automate the thermogram analysis. Paper [7] also discusses the use of deep learning, various applications of thermography, types of infrared cameras, and data presentation formats for analyzing thermographic data. The authors provide examples of case studies that combine thermography methods and deep learning on various platforms, such as UAVs, mobile phones, and embedded systems. In particular, they describe methods for processing thermogram sequences using neural networks. Such approaches can be applied to the tasks of classifying materials by their thermal properties.

The study [8] considers the possibility of using radiation in the infrared spectrum as a specific material property for its classification. The authors propose to classify materials by type with specific algorithm, combining data from optical and infrared sensors. The SVM method is used for classification. The results of testing on real data show a significant improvement in the reliability of material recognition.

In [9], the authors propose an approach to combining infrared thermography with machine learning. According to the described method, a laser source stimulates the surface of an object, while an infrared camera captures its thermal signature. Software algorithms find the features of these signatures and pass them on to a classification algorithm that is decision tree-based. This method has demonstrated an increase in classification reliability.

Task statement. The aim of the study is to develop and evaluate a method for automated classification of materials based on temperature profiles obtained by laser thermography using deep learning models.

Description of the thermographic method of material classification. Thermographic data can provide information about the material properties of an object of study by analysing how the temperature gradient on its surface changes over time and space. Heat propagation is described by the thermal conductivity equation, which includes a proportionality constant between the time derivative of the temperature and the spatial Laplace distribution. This constant is the thermal conductivity of a material, which reflects the ratio of its thermal conductivity to its volumetric heat capacity and indicates the ability of a material to conduct heat compared to its ability to store it. Different materials will heat and cool differently, which can be the basis for their automated classification.

The method of non-contact material type classification using thermography and machine learning can be described as follows: the object under study is heated using a laser source. A thermal imager records the heating and cooling of the object's surface. As a result, a sequence of thermograms is obtained that reflects the change in the thermal field of the object's surface over time. This sequence can be used to create a training data set.

To classify an object by type, one-dimensional temperature profiles in the pixels of the thermogram rather than two-dimensional images are sufficient to analyse. In other words, the diagnostic features will be formed based on the analysis of the nature of temperature changes at certain points on the object's surface during the heating and cooling procedure. The resulting temperature profiles are transferred to a model machine learning for further classification. The output of such a model will be a class label to which the system has assigned the thermal profile. To increase the reliability of the classification, it is necessary to analyse temperature profiles from several different points on the object's surface.

The scheme for implementing this approach is shown in Fig. 1. The flash controller control module instructs to generate a laser beam with the required duration and time waveform. The laser source heating, in turn, converts the electrical signal into a signal. A point actuator directs the generated optical signal to the sample. The actuator is controlled by the control module to perform heating at a precisely defined point. The thermal imager records a sequence of thermograms with a specified time interval between them. The data is sent to the module temperature profile, where classifications are analysed at the point heated by the laser. These profiles will differ for each type of material.

The temperature profiles of different materials can be very similar or overlap in some areas, which leads to a loss of reliability when using classical classification algorithms. For this reason, machine learning methods are recommended for automatic classification of temperature profiles. However, classical methods, such as decision trees or SVMs, have low noise immunity and do not perform well in time sequence analysis tasks, such as temperature profiles [10]. A more promising tool is deep learning methods – neural networks, which are widely used in data mining. The goal is to create a model that predicts the value of an object's class label based on the analysis of temperature profiles.

Thus, the temperature profiles will serve as input data vectors for the classification model, which will provide labels of the corresponding material classes as output. The number of hidden layers and neurons in them is selected experimentally during training and depends on the complexity of a particular task (number of material classes, presence of noise, etc.). It should be noted that one of the disadvantages may be the need for a large amount of training data for effective model training.

Description of deep learning models. Historically, the architecture of neural networks (NN) for classification tasks has been the first and most studied, as well as feedforward networks. Such networks provide for signal propagation in only one direction: from input to output. In the architecture of feedforward NN, there are no feedback loops, i.e., the output values of any layer do not affect this layer. This type of network is usually widely used for pattern recognition and signal classification and is described in detail in [11].

The main disadvantage of these networks in the task of classifying temperature profiles is that they consider all elements of the input vector as separate

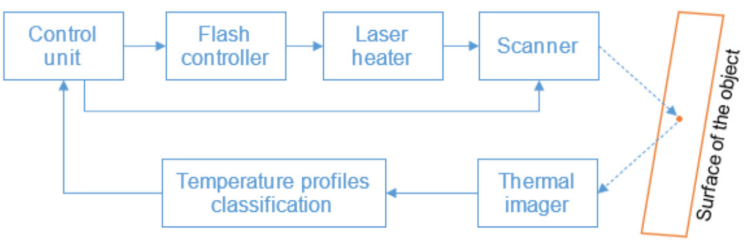


Fig. 1. Scheme of implementation of the thermal method for determining the type of material

and independent. However, temperature profiles are time sequences that reflect the nature of temperature change over time. Therefore, it is important to consider the relationships between measured temperature values within a temperature profile.

Long short-term memory (LSTM) is a type of recurrent neural network specially designed to work with data sequences and solve problems related to the loss of information in long sequences. The architecture of this class of networks is described in [12]. This architecture allows the model to store and use information for a long period of time, which makes it effective for tasks where the important context depends on a large number of previous elements of the sequence. Since the temperature profile is a time series that reflects the change in the temperature of an object's surface over time, LSTM is a promising architecture for use in this task.

The LSTM architecture has a number of modifications. One of them is Bidirectional Long Short-Term Memory (Bi-LSTM), a modification specifically designed to work with data sequences and solve the problem of context loss in areas where both forward and backward information is important. Bi-LSTM allows you to use information in both directions in time, which increases its ability to model complex dependencies in sequences. A full description of this architecture can be found in [13]. Potentially, bi-directional analysis of temperature profiles can improve the quality of their classification.

Another modern deep learning model for classifying time sequences is 1-D Convolutional Neural Networks (1-D CNN). This class of models is a variant of convolutional neural networks designed to process one-dimensional data sequences, such as time series or text data. The main idea is to use convolutional networks to detect local patterns or features in the input sequences. A full description of the 1-D CNN architecture can be found in [14].

Simulation modelling. In order to generate a training data set and test the described method of automated classification of materials by type, we performed simulation modelling of the process of heating and cooling samples from different materials. The COMSOL Multiphysics environment was used for the simulation. Four materials were selected for the study: Wood (pine), Acrylic Plastic, Steel, and Aluminium.

The samples are typical objects of interaction in teleoperation manipulation tasks – small in size and made of solid rigid materials. Geometrically, the samples are rectangular parallelepipeds with a height and width of 100 mm and a variable thickness from 1 to 30 mm. The thermophysical characteristics of each material were taken from the built-in COMSOL library.

To simulate the heating of samples, the COMSOL physics interface Heat Transfer in Solids is used. It is designed to simulate heat transfer by conduction, convection, and radiation. By default, the Solid model is active in all domains and will be used for solid materials. In all dimensions of space, steady-state, frequency domain, and time domain simulations are supported. Since we are modeling heating over a finite time interval, we will use time-domain modeling. The following modules were used in the heating simulation: Solid, Initial Values, Deposited Beam Power, Heat Flux

Solid. This module applies the heat equation to model heat transfer in solids:

$$\rho C_p \frac{\partial T}{\partial t} + \rho C_p u \cdot \nabla T + \nabla \cdot q = Q,$$
$$q = -k\nabla T, \tag{1}$$

where ρ [kg/m^3] is the density of the solid; C_p [J/(kg-K)] is the heat capacity of the solid at constant pressure; k [W/(m-K)] is the thermal conductivity of the solid; u [m/s] is the velocity field defined by the Translational Motion subnode (in the case when parts of the model move in the material frame); Q [W/m^3] is the heat source.

Initial Values. This block sets the initial value for the temperature, which can be used as an initial condition for transient modelling. We set the standard value, which is approximately room temperature, to 293.15 °K (20 °C). This setting is set for the entire sample body.

Deposited Beam Power. This module simulates a heat source that transfers energy to a given face through laser beams. The Beam orientation parameter is used to set the beam orientation **e**. In our case, the beam will be directed along the y-axis.

In the Beam profile section, parameters such as the value of the superimposed beam power P_0 [W] and the coordinates of the beam start point O[m] are set. was set by the function $P_0 0.05 \cdot \text{step1}(t)$, i. e. 50 mW per *step1*. Step 1, in turn, is a function of time, which changes from one to zero at 0.4 seconds in the time domain.

The beam distribution type Distribution type was selected as Gaussian. Thus, the sample is heated for 0.4 seconds by a 50 mW laser beam with a Gaussian distribution:

$$f(O,e) = \frac{1}{2\pi\sigma^2} \exp\exp\left(-\frac{d^2}{2\sigma^2}\right),\ d = \frac{\|e \times (x - O)\|}{\|e\|}, \tag{2}$$

where σ [m] is the standard deviation (in this study – 0.3 mm paper).

Heat Flux. This module is used to add heat flux through the faces of the sample. It applies to all faces. The Material type parameter indicates whether the input data is defined in material or spatial boundaries. The Solid option indicates that the heat flux q_0 is defined in material boundaries. In the settings of the Heat Flux itself, Convective Heat Flux was selected, which is described by the equation:

$$q_0 = h \cdot (T_{ext} - T), \tag{3}$$

where: $h\left[\dfrac{\text{W}}{\text{m}^2\text{K}}\right]$ – heat transfer coefficient; T_{ext} [K] – outdoor temperature; T [K] – object temperature.

The default option also allows you to enter a user-defined value for the heat transfer coefficient h $\left[\dfrac{\text{Вт}}{\text{м}^2\text{К}}\right]$. In our case, it is equal to 5.

An example of the obtained distribution of the thermal field of the surface of a steel sample 30 mm thick before and after heating can be seen in Fig. 2.

Description of the training data set. Based on the results of the simulation, a dataset was created in the form of temperature profiles for the classification of four types of materials. The data set includes temperature profiles of samples of all ten thicknesses for each material. The temperature values were monitored at five different points on the sample surface for two seconds in 2-millisecond increments. Thus, each temperature profile vector consists of 100 elements. The measurement points were located in the centre of the laser beam imprint and in its vicinity. Graphs of all the obtained temperature profiles during fifty measurements for each material can be seen in Fig. 3.

In total, the modelling resulted in a dataset of 200 samples, which was subsequently used to train neural networks. This volume is considered to be small, which makes training difficult. Also, based on the above graphs, we can conclude that many temperature profiles are of the same type, forming a certain lack of unique data, which can also negatively affect the efficiency of NN. In addition, we can observe that the indicators of wood with plastic and steel with aluminum are very similar, which further complicates the classification.

Model training. Most of the training parameters were the same for all models. Adam was chosen as the optimizer with a learning 0.00001 rate. The loss function was the standard for the classification of categorical cross-entropy. Accuracy was used as a metric criterion. The training dataset was used as a test set of 15 % of the samples.

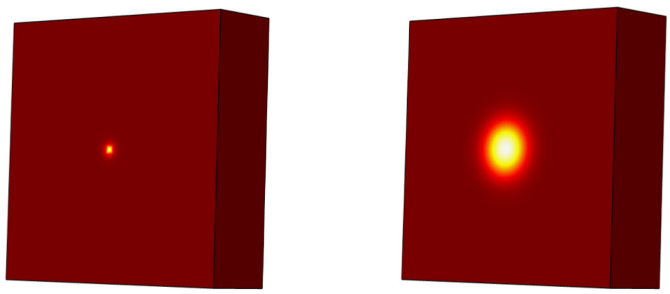
The models were trained using the Keras framework. The architecture of the models was chosen experimentally. The best results were obtained with the architectures shown in Table 1.

The number of samples in the training dataset was relatively small. Therefore, many epochs had to be used to train the models efficiently. Information about the number of hyperparameters of the implemented models, the number of training epochs, and the training results obtained on the test set is given in Table 2.

Discussion. As can be seen from Table 2, the highest percentage of correct answers was achieved in the Feedforward network. Compared to the other architectures, it also has the minimum number of epochs, which has a positive effect on the time required for its training. On the other hand, a large number of parameters reduces the model's performance.

The LSTM architecture has a slightly larger number of epochs than the other networks but a significantly smaller number of parameters, which, in practice, will mean a shorter training time and faster performance than other networks. However, the smallest percentage of correct answers casts doubt on its effectiveness in this task.

The Bi-LSTM network to train took fewer epochs than the baseline LSTM. Together with a small number of parameters, the network will learn and



a) b)

Fig. 2. Thermal field of the surface of a steel sample: *a* – at the beginning of heating; *b* – at the end of measurement

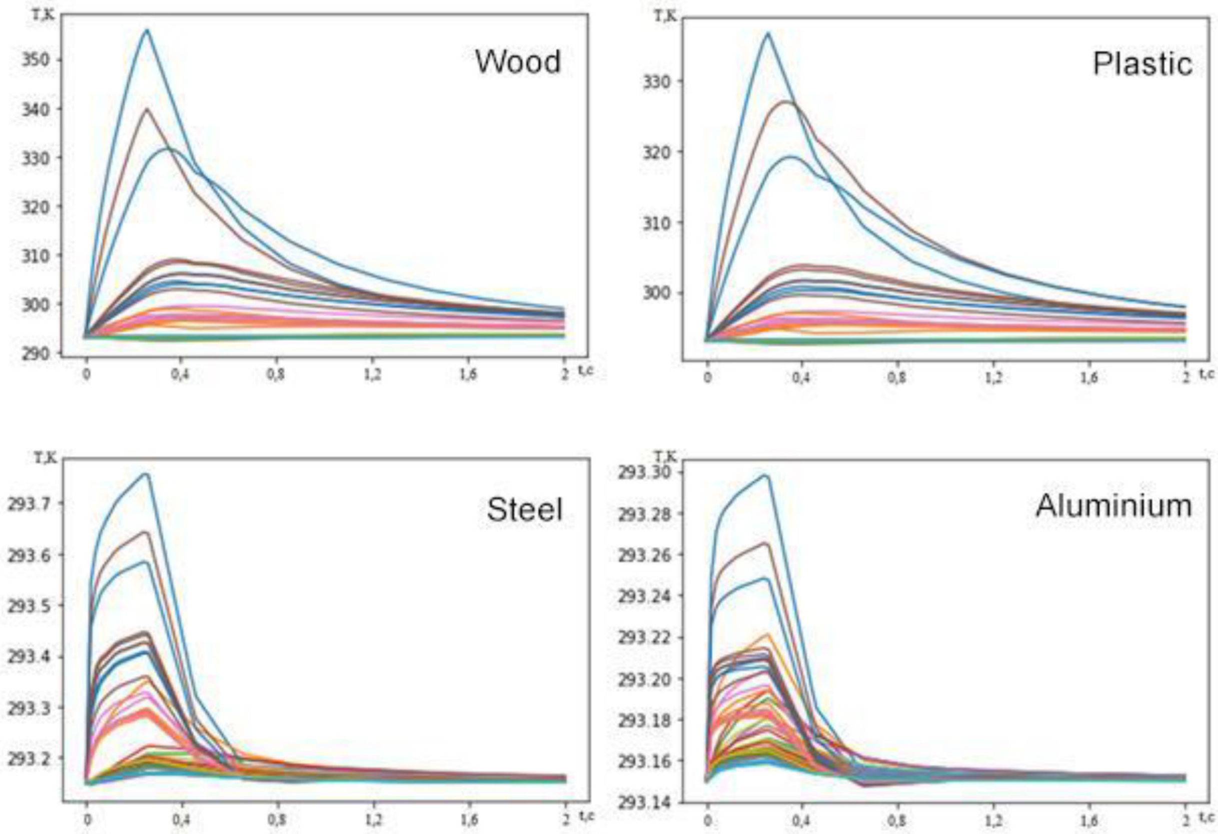


Fig. 3. Combined graph of the obtained temperature profiles of the samples

Table 1

Selected model architectures

Feedforward		**LSTM**		**Bi-LSTM**		**1-D Convolutional**	
Layers	*Output shape*	*Layers*	*Output shape*	*Layers*	*Output shape*	*Layers*	*Output shape*
Input	(100)	Input	(100,1)	Input	(100,1)	Input	(100,1)
Dense	(800)	LSTM	(100,100)	Bi-LSTM	(100,200)	Conv. 1D	(97, 128)
Batch norm	(800)	Dropout	(100,100)	Bi-LSTM	(40)	Conv. 1D	(95,64)
Dense	(100)	LSTM	(30)	Batch norm.	(40)	Max Pool	(47, 64)
Batch norm	(100)	Dense	(200)	Dense	(4)	Conv. 1D	(45,32)
Dropout	(100)	Batch norm.	(200)	–	–	Flatten	(1440)
Dense	(4)	Dense	4	–	–	Dense	(200)
–	–	–	–	–	–	Dense	(4)

Table 2

Comparison of training results of the developed architectures

Network type	**Number of Parameters**	**Number of Epochs**	**Accuracy, %.**
Feedforward	163,904	1000	76,6
LSTM	63,924	1500	70
Bi-LSTM	121,544	1000	73,3
1-D Convolutional	320,588	1000	73,3

work quickly. The percentage of correct answers is not the best, but not the worst either.

The 1D-Convolutional network is similar to the Bi-LSTM network in its results – it also trains for the same number of epochs and shows the same percentage of correct answers. However, it has the largest number of parameters of all the created architectures, so compared to Bi-LSTM, it will be slower to learn and perform.

According to the Table 2, it can be concluded that the multilayer feedforward network was the most accurate of all developed ones. The relatively large number of parameters negatively affects its performance, but this is not a decisive criterion in

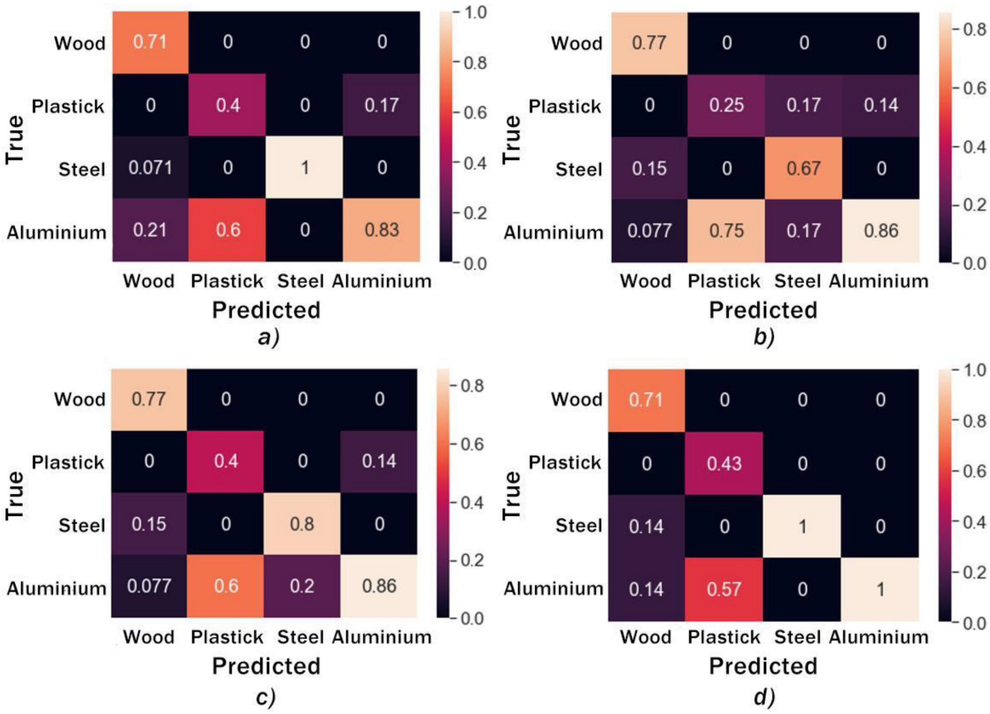


Fig. 4. Confusion matrices of models: *a* – Feedforward; *b* – LSTM; *c* – Bi-LSTM; *d* – 1-D Convolutional

the task of automated classification of materials by type.

The metric Accuracy provides a general understanding of the quality of the model. However, for a deeper understanding, it is also important to analyze the proportion of correct answers in the network for each class separately. For this purpose, confusion is used matrices. An error matrix displays all false and correct answers of the network for each class. The error matrices for each of the created models are shown in Fig. 4.

In terms of overall Accuracy, 1-D Convolutional is inferior to the multilayer direct propagation network, but this model has the best performance in terms of the error matrix. Thus, the network recognized two of the four classes (aluminum and steel) correctly. The model also has the highest classification plastic accuracy rate. Therefore, the final decision on the choice of a model for automating the process of classifying materials by temperature profiles should be made, taking into account all the features of the task.

We can conclude that networks are of particular interest for further research are Feedforward and 1-D Convolutional. The former has the best score accuracy, while the latter has the best error matrix. The training time of both networks is approximately the same. The 1-D Convolutional network has more parameters and takes up more memory space.

In general, all of the considered deep learning models demonstrate high classification accuracy rates, given a limited and monotonous training data set. In the future, attention should be paid to expanding the training dataset and optimising the chosen architecture of the deep learning model for classification.

Conclusions. Given the shortcomings of existing methods for determining the type of material, it is advisable to use thermography. The thermal method simplifies the classification, reduces the time required for its implementation, and is easier to automate. Since the pattern of heating and cooling a material creates a unique temperature profile that is specific to a particular type of material, it can serve as a reliable indicator for classification. The use of deep learning for automated temperature profiles can improve the Accuracy and efficiency of this process. Classification According to the results of training neural network models, the architectures considered in this paper showed a reliability of up to 76.6 %.

The proposed method can be used as part of robotic systems to solve the problem of determining the type of materials used in various industries and activities. An urgent task at the moment is to create an expanded set of training data in order to increase the reliability of material classification under different conditions measurements. It also promises to combine the analysis of temperature profiles and the nature of visual changes in the thermal field of the surface of the object under study. Convolutional neural networks can be used for automated analysis of thermograms.

Bibliography:

1. Liu H., Song X., Bimbo J. Surface material recognition through haptic exploration using an intelligent contact sensing finger. *Vilamoura*. 2012. pp. 52–57.

2. Chitta, S., Sturm, J., Piccoli, M., Burgard,W. Tactile sensing for mobile manipulation. *IEEE Trans. Robot*. 2011. No. 27. pp. 558–568.

3. Aujeszky T., Korres G., Eid M. Thermography-based material classification using machine learning. *EEE International Symposium on Haptic Audio-Visual Environments and Games*, Abu Dhabi, 3 March 2017.

4. Skladchykov I. O., Momot A. S., Galagan R. M., Bohdan G. A., Trotsiuk K. M. Application of YOLOX deep learning model for automated object detection on thermograms. *Information extraction and processing*. 2022. Vol. 2022, no. 50, pp. 69–77 DOI: https://doi.org/10.15407/vidbir2022.50.069

5. Saponaro P., Sorensen S., Kolagunda A. and Kambhamettu C. Material classification with thermal imagery *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2015. pp. 4649–4656. DOI: https://doi.org/10.1109/CVPR.2015.7299096

6. Галаган Р. М., Момот А. С., Протасов А. Г., Петрик В. Ф., Богдан Г. А. Тестування нейромережевих модулів системи теплової дефектометрії за допомогою імітаційного моделювання. Вчені записки ТНУ імені В. І. Вернадського. Серія: Технічні науки. 2021. № 6. с. 49–55. DOI: https://doi.org/10.32838/2663-5941/2021.6/08

7. Infrared machine vision and infrared thermography with deep learning: a review / Y. He et al. *Infrared physics & technology*. 2021. Vol. 116. P. 103754. DOI: https://doi.org/10.1016/j.infrared.2021.103754

8. Großmann W., Horn H., Niggemann O. Improving remote material classification ability with thermal imagery. *Scientific Reports*. 2022. Vol. 12, no. 1. DOI: https://doi.org/10.1038/s41598-022-21588-4

9. Aujeszky T., Korres G., Eid M. Material classification with laser thermography and machine learning. *Quantitative InfraRed Thermography Journal*. 2018. Vol. 16, no. 2. P. 181-202. DOI: https://doi.org/10.1080/17686733.2018.1539895

10. Application of support vector machine for pattern classification of active thermometry-based pipeline scours monitoring / X. Zhao et al. *Structural Control and Health Monitoring*. 2014. Vol. 22, no. 6. P. 903–918. DOI: https://doi.org/10.1002/stc.1724

11. Goodfellow I., Bengio Y., Courville A. Deep learning. Frechen: MITP, 2018. 801 p.

12. Murugesan R., Mishra E., Krishnan A. Deep Learning Based Models: Basic LSTM, BI LSTM, stacked LSTM, CNN LSTM and CONV LSTM to forecast agricultural commodity prices. 2021. 32 p. (Preprint). DOI: https://doi.org/10.21203/rs.3.rs-740568/v1

13. Zhao C., You J., Wen X., Li X. Deep Bi-LSTM Networks for Sequential Recommendation. *Entropy*. 2020. Vol. 22, no. 8. P. 870. DOI: https://doi.org/10.3390/e22080870

14. 1D convolutional neural networks and applications: A survey / S. Kiranyaz et al. *Mechanical Systems and Signal Processing*. 2021. Vol. 151. P. 107398. URL: https://doi.org/10.1016/j.ymssp.2020.107398

Момот А. С., Наконечний М. В., Галаган Р. М., Муравйов О. В. АВТОМАТИЗОВАНА КЛАСИФІКАЦІЯ МАТЕРІАЛІВ НА ОСНОВІ ТЕМПЕРАТУРНИХ ПРОФІЛІВ

У статті представлено метод автоматизованої класифікації матеріалів на основі аналізу їхніх температурних профілів. Використання лазерної термографії в поєднанні з алгоритмами глибинного навчання дозволяє здійснювати безконтактне розпізнавання типу матеріалу з високою точністю. Це особливо актуально для робототехнічних систем, які виконують маніпуляційні операції, автоматизований контроль якості та технічну інспекцію без фізичного контакту з об'єктом.

Огляд попередніх досліджень показав, що існуючі методи класифікації матеріалів мають певні обмеження. Візуальні методи можуть бути ненадійними через залежність від умов освітлення та схожість зовнішнього вигляду різних матеріалів. Контактні методи забезпечують високу точність, але вони складні у реалізації та вимагають фізичної взаємодії, що не завжди є доцільним у робототехніці. Тому термографічний підхід є перспективним, оскільки дає змогу визначати тип матеріалу за його реакцією на нагрівання та охолодження.

У роботі описано експериментальну систему, яка використовує лазерний промінь для нагрівання поверхні об'єкта, після чого тепловізор реєструє зміну температури у часі. Отримані температурні профілі аналізуються за допомогою методів машинного навчання. Виконано моделювання процесу теплопередачі для чотирьох типів матеріалів (дерево, пластик, сталь, алюміній) у середовищі COMSOL Multiphysics, що дозволило сформувати навчальний набір даних.

Для класифікації температурних профілів протестовано чотири архітектури нейронних мереж: Feedforward, LSTM, Bi-LSTM та 1D-Convolutional. Найкращі результати продемонструвала Feedforward-мережа, яка досягла долі правильних відповідей на рівні 76,6 %. Встановлено,

що температурні профілі деяких матеріалів мають значну схожість, що ускладнює класифікацію, тому подальші дослідження мають бути спрямовані на розширення набору навчальних даних та оптимізацію архітектури моделей.

Запропонований підхід має широкий спектр застосувань у промисловості та робототехніці, де потрібна швидка ідентифікація матеріалів без фізичного контакту. Автоматизована система класифікації матеріалів на основі температурних профілів може підвищити ефективність технологічних процесів, покращити безпеку виробництва та розширити можливості автономних роботизованих комплексів.

Ключові слова: *класифікація матеріалів, лазерна термографія, машинне навчання, нейронні мережі.*