

Towards Information Flows in Recognition and Prediction Tasks with Internet of Things

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Abstract. This paper describes the possibilities of communication through information flows in the tasks of recognition and prediction using the example of assessing the change in the state of defects in materials. In the context of communication between several system elements, an important part is the formation of adequate information flows and optimal messages. In this context, the grouping of information according to the principle of informativeness is proposed, using the example of the problem of recognition and further forecasting. Information transfer with the Internet of Things involves exchange over wireless networks and network protocols. In the paper, it is proposed to use the segmented area of the recognised object to check the forecast. The paper proposes to use the segmented region of the recognised object in the image and use it to check the prediction. In addition, sensor data can be utilised to test defect classification. This design of information flows can improve performance.

Keywords: information flow; object recognition; predictive analysis; Internet of Things; information technology.

INTRODUCTION

Between several parts of a monolithic or distributed system, there is an exchange of information about the current state of a particular object and the actions that can be performed. During this communication, information flows must be optimal in size and have a certain informativeness. Often, images are processed in recognition tasks, and the result should be an optimal message. When transferring, questions usually arise about insufficiently efficient transfer time, a large volume of messages, and others. Both for recognition and for forecasting, the application of machine learning methods is a promising direction. In recognition, testing the trained network based on a test data set is essential. On the border of these tasks, it is necessary to correctly transform the data and translate it into the required format.

This paper aims to form a set of main features and methods of optimising and grouping information in messages for recognition tasks and further predict the change in the state of the defect.

The main tasks in the work are the following: comparison of message grouping efficiency

considering the informativeness and size of the message; analysis of the process of transforming information from a processed image into admissible for prediction when using the Internet of Things.

MATERIALS AND METHODS

The basis of the study of the problem is the concept of information flow as a process of data transfer between several elements in information technologies. Based on pattern recognition, paper [1] shows the possibility of data transfer based on flow. In [2], when applying machine learning based on the U-Net architecture, a model of mutual information between levels is proposed, which explains information flows through different parts of the same system. If the prediction of the change in the state of defects is based on classification, then it is shown how information flows can work for this task [3]. As described in work [4], information exchange stages occur from data collection from external sensors through information processes to decision-making systems. In the middle of systems, communication can also

occur between different interfaces or parts by analogy, as it can be implemented in technological processes [5]. In the context of the Internet of Things [6, 7], we considered reducing the load on cloud services through data grouping. This may mean that, in general, the concept of information flows and their interaction in the system occupies an integral part of effective functioning.

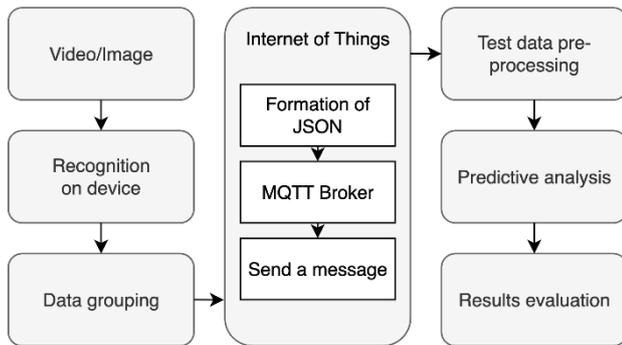


Figure 1 – Visualisation of the interaction in recognition-prediction tasks

In general, the design tasks of recognising and predicting changes in the object's state can be implemented, as shown in Fig. 1. Sending texts or voice information streams today is rapidly developing and becoming capable of floating on other systems. Still, the most popular and most accessible to use are photos and videos. The input parameter is information about the number of pixels of the found defect in the image and data from sensors about the environment. However, there may be many more information streams. One of the stages for counting the number of isolated pixels is recognition on the device. The program on the device can highlight individual areas of the defect based on computer vision methods, and it is possible to remove unnecessary things from the background or with blurring. After that, the data is grouped to reduce the requests to the central receiver. Data is grouped for more accessible work with them and increased transfer speed. The next stage is one of the most critical components of the Internet of Things. Such a term is very generalised. That is why you can see specific stages of information flow in the middle of such a block. First, the data is formatted in JSON format. Such a template allows you to work with data when sending and receiving data freely. The last step is sending the message to the server. After data processing, this part uses environmental data as test data and prepares it for prediction. The next stage is the

classification of accurate data with historical combinations of previous similar events. The final step is to check the prediction result with data on the number of found pixels with a defective image.

RESULTS AND DISCUSSION

Comparison of methods grouping of the message. When recognising directly on the reading device, you can select an object and use the information about the number of pixels of the segmented object as a quantitative measure. As an example of defects in materials, cracks [8] or corrosion [9] can be considered, which can be detected based on computer vision methods.

Data can be forecasted in the time domain or when classifying into a particular group. For a problem with defects, it is possible to determine from a set of parameters whether there were defects or not according to historical data. In addition, to select the most essential characteristics that are most correlated with each other, it is possible to carry out feature engineering. To perform forecasting, learning takes place based on historical data. Testing the trained network can already take place for accurate data classification.

Moreover, data about the environment (moisture, temperature) can be input into the system to evaluate the change in the state of defects. In that case, the output can be data about the potential presence or absence of a defect based on historical data. Mutual communication between parts of the system is based on exchanging information, which can be implemented on the Internet of Things. The result of image processing, the number of pixels of the segmented area, is transmitted to the system for prediction verification. In this way, it is possible to assess the criticality of the defect using certain conditions and rules.

Among the well-known image compression metrics, there is the Structural Similarity Index (SSIM) [10]. Moreover, sending whole images can be quite voluminous, even with compression. This metric can help evaluate image quality deterioration after compression or transmission. Some compression methods can be affected by the loss of details in the image and, as a result, incorrect recognition at the final stage [11].

The amount of information that can be sent, even in grayscale, may require 106 bits for images with a resolution of 512 by 512. If the already processed image processing result is sent as an

integer value of the number of pixels from IoT, then 16 bits or 32 bits, depending on the bitrate of the operating system. This way, the load on the central server with the MQTT broker is reduced, and only the most necessary information is allocated [12, 13, 14, 15].

Analysis of the process of transforming information. An API or MQTT broker can request the flow of information in terms of interaction in IoT. Information flows are built both inside the device and through external connections. The internal exchange of information can be implemented within the framework of data processing programs and the advancement of predictive information analysis.

In general, information flows can be divided into several (Fig. 2):

1. Data processing and transfer from the reading device to the data storage.
2. Data from historical data is used to train a classifier with the ability to predict changes in the state of a defect in the material.
3. Mutual exchange of information in forecasting and recognition tasks in which the number of segmented pixels to check the classifier (present or absent defect according to historical data).

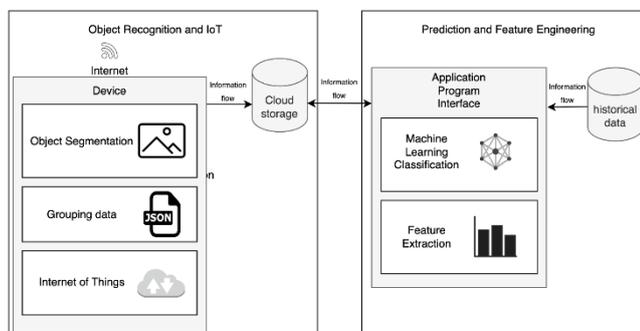


Figure 2 – General diagram with information flows in recognition and prediction tasks

Fig. 2 shows the division of the information flow into two stages. Of course, these two stages are closely related because they interact through the exchange of information. In the first stage, there is object recognition and work on the side of the Internet of Things. A connection to the Internet is necessary, which helps exchange information

between the device and the remote cloud storage. Image objects are segmented on the device side. The next stage is grouping data and ensuring connection and exchange of information with cloud storage. The second stage is the implementation of predictive analytics. Machine learning classifiers are used to determine and process input and test data at this stage. In addition, after obtaining the result, the display of the results and their saving should be applied.

Different structures and dependencies of parts can be formed at the junction of these two tasks of object recognition and prediction based on classification. Still, the efficiency of information flows should be taken into account. The considered problem can be helpful when the received information is valuable purely about the object and the area occupied by it in the image. In this way, when sending video frames, the number of highlighted pixels can be tracked, which can be used to analyse the criticality of the object based on data about surface defects in perspective.

The results can be more effective using more accurate recognition algorithms and more trained machine learning classifiers. However, more attention is paid in this work to information flows and mutual communication between different parts of the proposed system.

CONCLUSIONS

This paper describes possible methods of communication between several parts of the system, which include the recognition and prediction of changes in the state of an object. The main differences and defining features of forming information flows between these parts are highlighted. The methods of grouping that can be applied for data compactness and reducing the load for accumulation in data warehouses are considered. In addition, the leading information flows that can function are shown in the prominent examples of information exchange between parts of the problems of recognising and predicting material defects. It is proposed to transmit grouped numerical information instead of image bytes to improve the speed of data exchange between the described two parts.

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