Development of automated system based on neural network algorithm for detecting defects on molds installed on casting machines

V Yu Bazhin, I V Danilov, P A Petrov
Saint Petersburg Mining University, 2, 21 line of V.I., Saint Petersburg, 199106, Russia
E-mail: iliyavdanilov@yandex.ru

Abstract. During the casting of light alloys and ligatures based on aluminum and magnesium, problems of the qualitative distribution of the metal and its crystallization in the mold arise. To monitor the defects of molds on the casting conveyor, a camera with a resolution of 780 x 580 pixels and a shooting rate of 75 frames per second was selected. Images of molds from casting machines were used as input data for neural network algorithm. On the preparation of a digital database and its analytical evaluation stage, the architecture of the convolutional neural network was chosen for the algorithm. The information flow from the local controller is transferred to the OPC server and then to the SCADA system of foundry. After the training, accuracy of neural network defect recognition was about 95.1% on a validation split. After the training, weight coefficients of the neural network were used on testing split and algorithm had identical accuracy with validation images. The proposed technical solutions make it possible to increase the efficiency of the automated process control system in the foundry by expanding the digital database.

1. Introduction
The process of light alloys casting, based on aluminum and magnesium, is the final stage of processing. A liquid alloy is poured into molds located on the belt of the casting machine[3]. After pouring, the mold with alloy passes a cooling line (water or air-water), and at the end of the conveyor belt with help of an operator with a metal rod, ingots are knocked out of the mold into the container under the belt.

Nowadays, there are filling machines with an open and closed casing. The difference between them is that with closed casing, molds are visible only at the point of casting and at the point of extraction of the ingot. Machines with an open casing are easy to set up an external cooling system and always have lower price. Nevertheless, machines with open casing have a big drawback: due to defects in molds, an emergency situation can occur, which external effect can injure personnel.

Defects of molds occur during the casting process, mainly with a prolonged cycle of abrupt heating and cooling. Evaluation of molds takes place either during technical or preventive work on the casting machine or during the extraction of the ingot by an operator.

Some casting machines have a mechanism for automatic ingot extraction. At the "cold" end there are 2 or 4 hammers, which are with a certain interval beat on the left and right side of the mold. If there are defects on the surface of the mold, standard force can be not enough to extract a bar and there
is a need for a person who will control this process and, in case of failure, one will manually knock out the ingot. Otherwise, metal may overflow an already filled mold.

Insufficient control over defects on molds can cause many problems in the technological process [2]. The formation of heat mesh, longitudinal and transverse cracks on the inner surface of the mold can greatly affect the final quality of the bar, which will not correspond to the technological instructions. Defects molds can also lead to emergency situation [6]. The chipping is a frequent defect in the molds of casting machines with an automated extraction mechanism. During the knocking out, the hammer strikes the boards with a strong impact. An example of such defect is shown in Figure 1.

![Figure 1. Chipping of the mold](image)

Real-time control included in automated production allows one to increase the safety of process management, maintenance personnel, as well as to exclude the human factor in assessing the state of the mold surface.

2. Development of the automated defect recognition system

As a solution of the problem, it is proposed to develop a system for automated determination of molds with defects with the ability to transfer information to the OPC server, with further transfer to the SCADA system of the site.

For image acquisition, the machine vision camera of Basler acA780-75gc [8] was chosen. The selected camera has the ability to shoot in a mode of 75 frames per second and a color matrix, necessary for correct identification of defects. The camera is installed at the "cold" end of the filling machine. The images obtained with the camera of technical vision via Ethernet will be transferred either to the device acting as a local controller or directly to the operator's PC. As a possible version of the controller, the Raspberry pi 3 microcomputer is considered (Figure 2). Raspberry pi 3 supports Ethernet and the Linux operating system, on which the script of the neural network algorithm in Python 3 can be launched.

The choice of programming language Python 3 is based on a large number of open libraries, flexibility, simplicity and focus on machine learning [2]. The OpenCV2 library is used for image processing, NumPy is used to work with data arrays, and Keras with TensorFlow backend from Google is used to build the architecture and algorithm of the neural network.

![Figure 2. Raspberry Pi 3 microcomputer](image)
As a neural network architecture for determining molds with defects, it is decided to use a convolutional neural network (CNN), first proposed by Yan LeCun [7]. The architecture of the CNN was created by analogy with the biological mechanism of vision. The main components of the network topology are three layers: a convolution layer, a subsampling and a fully-connected layer. Each of them is engaged in its task.

A convolutional layer is the main component of the convolutional neural network. The first step specifies the kernel with a certain size in pixels. At the next stage, the kernel starts to move along the original image with a certain step, and at each step the scalar product of the kernel and pixels in the original image will be calculated. Pixels that are close to each other have a greater mutual influence in the formation of the feature than the pixels located in opposite corners. After passing the kernel through the image, the output is the so-called "feature map".

Each kernel can be considered as a feature identifier, which has a pixel structure in which the numerical values of the pixels, which define the property, are the biggest. An example is shown in Figure 3.

![Feature map](image)

Figure 3. Feature map

One more important layer in the CNN is the subsampling layer. Each area of the image with a certain size (often 2 by 2 pixels) is replaced by the maximum pixel value in this area. As a result, instead of 4 pixels there is only 1. This operation reduces the dimension, and, consequently, saves the processing power of the system. An example of the operation of a subsampling layer is shown in Figure 4.

![Subsampling on 4 x 4 image](image)

Figure 4. Subsampling on 4 x 4 image

The Dropout regularization layer [5] for a convolutional neural network allows the algorithm to be protected from overfitting. Overfitting is the adjusting of the neural network to a specific set of training data, in which the network will work correctly with the only data set. Dropout with parameter $p$ for one iteration of training passes through all neurons of a certain layer and with probability $p$ completely excludes them from the network during the iteration. Using the Dropout layer, the neural network will rely on the "unified view" of the neurons within one layer.

The last layer of CNN is a fully-connected layer [4]. The principle of its work is to access the output of the previous layer (which displays high-level feature maps) and to match specific properties with a certain class. A fully-connected layer estimates the strength of the connection between a high-level function and a particular class. As a result, during the calculation of the product of weights with the previous layer, the correct probabilities for different classes are determined.

The developed neural network architecture for determining molds with defects contains 10 convolutional layers, 5 subsampling layers and 5 dropout layers. The first fully connected layer
contains 1024 neurons, and the last one has only one neuron (“1” - there is a defect, “0” - there is no defect). The topology of the neural network is as follows:

1. The convolution layer
2. The convolution layer
3. The sub-sampling layer
4. Dropout Layer
...
(this construction is repeated 5 times)
...
21. The fully-connected layer (1024 neurons)
22. A fully-connected layer (1 neuron, if "0" - there is no defect, if "1" - there is a defect)

For neural network training, 200 images of molds from casting machines were processed (examples in Figure 5). For testing, 50 photos of molds that were not in the training sample were used.

![Figure 5. Images of molds: a) mold without defect, b) mold with defect](image)

3. Results analysis
After the training on the test sample, the accuracy of identification of the mold with a defect was 95%. The remaining 5 percent of incorrect recognition can be caused by shadows due to uneven lighting in the foundry and small cracks that were not recognized by the algorithm or camera.

Due to obtained results, it is expected that the introduction of such system will allow one to determine the defect formed during the casting process with a high probability in a timely manner and take the actions necessary in a particular situation (stopping the process, replacing the mold, increasing the force of the hammers).

4. Conclusion
During the research, the algorithm for automated detection of molds with defects on the filling machine line was developed.

The absence of real solutions for the control of defects that would exclude the human factor and allow timely identification of a defect proves the urgency of solving the described problem. On the first stage, the equipment for image acquisition and processing was selected and an algorithm for neural network identification of molds with defects on the moving belt of the casting machine on aluminum production was developed. The accuracy of identification was 95.1%. Large cracks, which represent the greatest danger, appear due to the expansion of smaller cracks. The formation of large cracks from small ones takes some time, during which defects on the mold surface will be detected by the developed system during several passes of the belt.

Integration of the developed system into real foundry will allow reducing the amount of defect ingots and increasing the safety of production by timely identifying defects in molds for molding and operator will be timely informed about the occurred.
References
[1] Dronov V, Prohorenok N 2016 Python 3. All necessary things. (BHV-Petersburg) p. 30-70
[2] Ivanov M A, Kulakov B A, Shvekov V I 2016 The influence of casting technological parameters on mold resistance (Bulletin of the South Ural State University).
[3] Y.A. Kurganova, S.P.Scherbakov 2017 Effect of a discrete additive of aluminum oxide on the structure and properties of an aluminum alloy (Journal of Mining Institute Т. 228). p. 717-721.
[4] Raschka S 2015 Python Machine Learning. 1st Edition (Packt Publishing)
[5] Tarhov D 2014 Neuronet models and algorithms (Radiotechnika)
[6] Cheh A 1964 Investigation of factors affecting the life cycle of molds (Proceedings of the 28th International Congress of Foundry)
[7] LeCun Y, Boser B, Denker J S, Henderson D, Howard R E, Hubbard W and Jackel L D 1989 Backpropagation Applied to Handwritten Zip Code Recognition (Neural Computation), pp.541-551
[8] Machine vision cameras. Balser [Web-site] Basler AG, 2018. URL: https://www.baslerweb.com/ru/ (Date: 18.12.2017)