DEVELOPMENT OF A STRUCTURE AND ALGORITHM BASED ON NEURAL NETWORKS FOR THE DETECTION AND ANALYSIS OF UNDERGROUND DEPOSITS

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Annotation. *In the last decade, artificial neural networks and machine learning have become the most used areas for solving complex real-world problems. In particular, problems that are considered too difficult or in some cases impossible to solve with computers are of increasing interest in both academia and industry. This paper considers the digital processing of one- and two-dimensional signals using an artificial neural network. Neural networks are based on the so-called activating function of neurons. This feature is critical to network performance but is often neglected . In most cases, one of the non-adaptive functions is chosen as the activation function. Adaptive sigmoid or ReLU functions are used in many cases, but these functions have disadvantages because adapting data from one limited area affects the overall results. Therefore, the paper proposes the use of flexible quadratic B-spline functions with free nodes. Spline is an activation function that expands the scope and exactly satisfies the approximation condition. This prevents overfitting in neural networks. Including the recurrence property of splines corresponds to the structure of recurrent neural networks.*

Keywords: *ReLU, neural network, bipolar coupling, monopolar coupling, spline functions, quadratic B-spline, piecewise-polynomial methods.*

INTRODUCTION

Today, scientists are conducting a lot of research in the field of geophysics. There are many difficulties, especially in determining underground mineral resources. Determining the depth of radioactive elements emitting radiation since the beginning of time has been a problematic issue until now. This issue solve for scientists by each different algorithms offer is being done. But above ground radiation from signals using the old man chemical of elements is located the place in prediction, today of the day being used model and in methods big errors presence because, new model and to methods need is felt . This of methods one with a car teaching In machine learning basically linear regression initial to be studied from algorithms one. Him various information to collections when applied various advantages and restrictions determined. It plays a key role in linking the linear relationship between local and global variables. As an improvement to this model, multivariate regression is used and it often gives better results. But using polynomial regression in data sets with high variability leads to overfitting. And when neural networks are built, they don't work well with the information in their hidden layers. Therefore, the use of regression spline functions is now defined. At the core of neural networks is the so called activation function of neurons. This function is the most important for the fast and accurate operation of the neural network. In many cases, adaptive functions are chosen as activation functions. For example, sigmoid or ReLU functions are used. Their main disadvantage is that the values of the functions always lie between 0 and 1. These values are more needed when solving logistic regression problems. In order to process signals and make predictions correctly, the use of these functions in neural networks leads to an increase in absolute errors in the approximation process. Therefore, we suggest using flexible spline functions with free nodes.

METHODS

Univariate B-spline functions are said to be defined with respect to the segments of a smooth curve connecting a set of node points. Each part of the spline between two consecutive nodes is called a slice. In each slice, the spline is represented by a polynomial function of degree **d** . In the framework of the quadratic spline K , it focuses on the second-order polynomials, d = 2.

$$B_{i,2}(t)=\frac{t-t_i}{t_{i+2}-t_i}B_{i,1}(t)+\frac{t_{i+3}-t}{t_{i+3}-t_{i+1}}B_{i+1,1}(t) \tag{1}$$

$$B_{i,2}(t)=\begin{cases} \dfrac{t-t_i}{t_{i+2}-t_i}\cdot\dfrac{t-t_i}{t_{i+1}-t_i}, & if\ \ t\in[t_i,\ t_{i+1}] \\ \dfrac{t_{i+2}-t}{t_{i+2}-t_{i+!}}\cdot\dfrac{t-t_i}{t_{i+2}-t_i}+\dfrac{t-t_{i+1}}{t_{i+2}-t_{i+1}}\cdot\dfrac{t_{i+3}-t}{t_{i+3}-t_{i+!}}, & if\ \ t\in[t_{i+!},\ t_{i+2}] \\ \dfrac{t_{i+3}-t}{t_{i+3}-t_{i+1}}\cdot\dfrac{t_{i+3}-t}{t_{i+3}-t_{i+2}}, & if\ \ t\in[t_{i+2},\ t_{i+3}] \\ 0, & акс\quad холда \end{cases} \tag{2}$$

If we open the above formula in the time interval [0, 3], the following expression will appear.

$$\frac{\partial r}{\partial w_i}=\frac{2}{N}\sum_{i=0}^{N}(\varphi_i(x)-y_i)\cdot\varphi_i(x)'$$
$$\frac{\partial r}{\partial w_{i+1}}=\frac{2}{N}\sum_{i=0}^{N}(\varphi_{i+1}(x)-y_{i+1})\cdot\varphi_{i+1}(x)' \qquad (3)$$
$$\frac{\partial r}{\partial w_{i+2}(x)}=\frac{2}{N}\sum_{i=0}^{N}(\varphi_{i+2}(x)-y_{i+2})\cdot\varphi_{i+2}(x)'$$

If we enter a value in the interval [0,3] with a step of 0.1, a graph in the form of Figure 1.1 will appear.

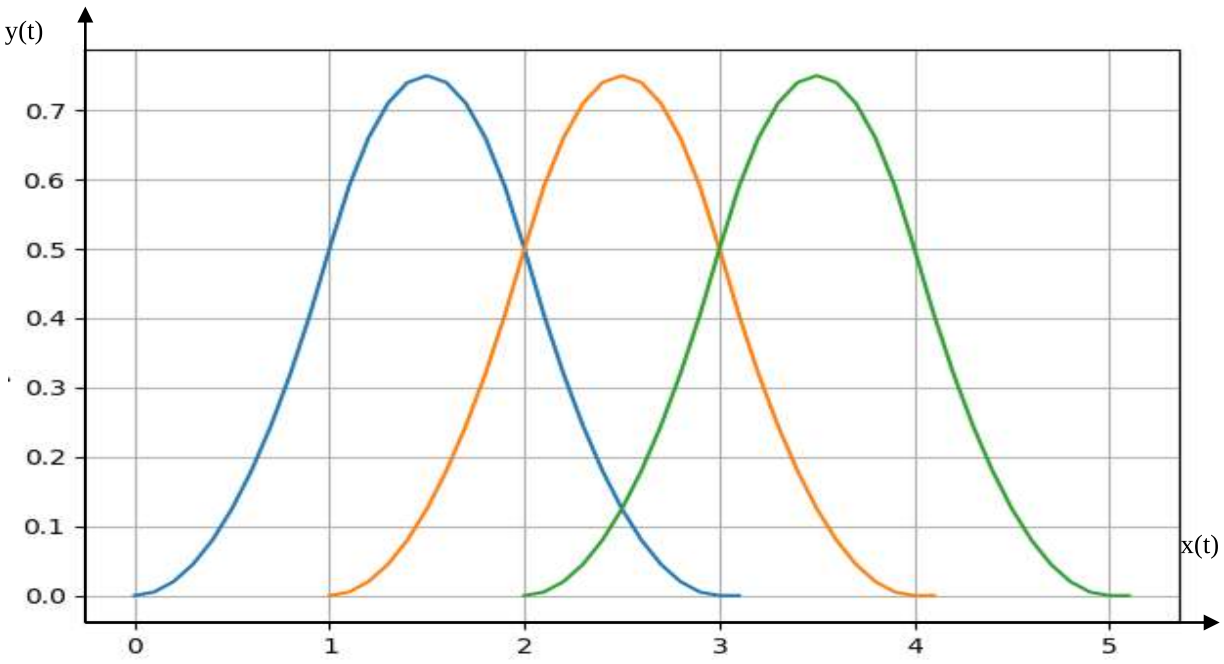

Figure 1. Repeating B-spline at intervals

The spline function iterates over every three intervals and recovers the value of the signals. In the process of restoring the value of the signals, it satisfies the approximation condition, and therefore this function is less accurate than the functions subject to the interpolation condition. Based on this function, we perform one-dimensional geophysical signal recovery.

$$c(t)=\sum_{i}^{i+d}Q_iB_{i,\,d}(t) \qquad (5)$$

$c(t)=\left[x_c(t),\; y_c(t)\right]$The coordinates of the spline curve evaluated at $\langle\vec{x};\;\vec{y}\rangle$t in the Cartesian coordinate system . Q_i - the coordinates of the nodal point, d - the degree of the parametric curve, $B_{i,\,d}(t)$d-degree mixed functions.

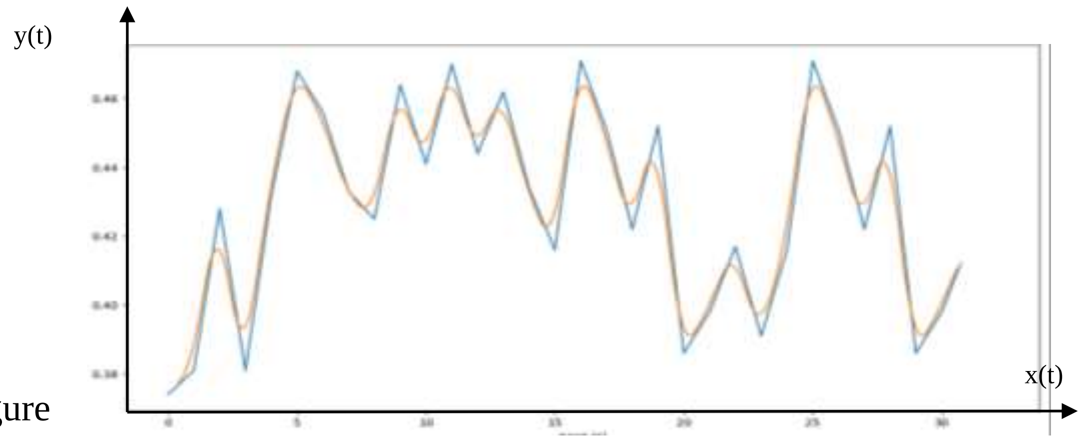

Figure 2.
Quadratic B - spline based univariate signal reconstruction

The graph above represents the approximation of the geophysical signal.

Table 1.

Results of approximation of one-variable geophysical signal on the basis of quadratic B-spline

No	$x_i(t)$	$B_i(t)$	No	$x_i(t)$	$B_i(t)$
1.	0.381000	0.377500	9.	0.451000	0.461000
2.	0.428000	0.404500	10.	0.422000	0.436500
3.	0.381000	0.404500	11.	0.452000	0.437000
4.	0.432000	0.406500	12.	0.386000	0.419000
5.	0.468000	0.450000	13.	0.398000	0.392000
6.	0.456000	0.462000	14.	0.417000	0.407500
7.	0.433000	0.444500	15.	0.391000	0.404000
8.	0.425000	0.429000	16.	0.416000	0.403500

Table dvgi $X_i(t)$ - the value of the incoming signal. B_i (t)-signal approximation results. In the above table Δ_1 - 0.0155 absolute error. Δ_2-3.5% relative error.

RESULTS

In B-spline functions of two variables the main factor is the separate organization of nodes along the main $\vec{x}$ and directions. $\vec{y}$ Indeed, to construct a parametric surface, it is essential to have an organized mesh network of nodes. Nodes correspond to a set of orthonormal coordinates of properly matched nodes $\langle \vec{x},\ \vec{y},\ \vec{z} \rangle$ [4; 2] .

$$S(u,v)=\sum_{i}^{i+d}\sum_{j}^{j+d}Q_{i,j}\cdot B_{i,d}(u)\cdot B_{j,d}(v) \qquad (6)$$

Here:

it is spatial of the system parametric the surface the first in the direction watching going internal parameter;

v is the internal parameter of the spatial system following the parametric surface in the second direction, $S(u, v) = [x_s(u, v); y_s(u, v); z_s(u, v)]$ the coordinates of the parametric surface in the Cartesian coordinate system evaluated at;

d-level of spline in both directions;

$Q_{i,j}$ - control point coordinates,

$B_{i,d}(u)$ and $B_{i,d}(v)$ are d-level B-spline functions for their respective internal parameters [1; 101] .

$S(u, v)$-is a function of class C ^{1} , since biquadratic splines guarantee the continuity of the first derivatives on all parametric surfaces except the boundaries. Quadratic Another property of B -spline functions is that it is repetitive at a certain point [2; 15] . This makes it possible to use it as an activation function in neural networks.

$S(u, v)$ is a function of class C ^{1} , since biquadratic splines guarantee the continuity of the first derivatives on all parametric surfaces except the boundaries. If two-dimensional signals are reconstructed using the formula (6) above, a graph in the form of figure 1.3 will appear.

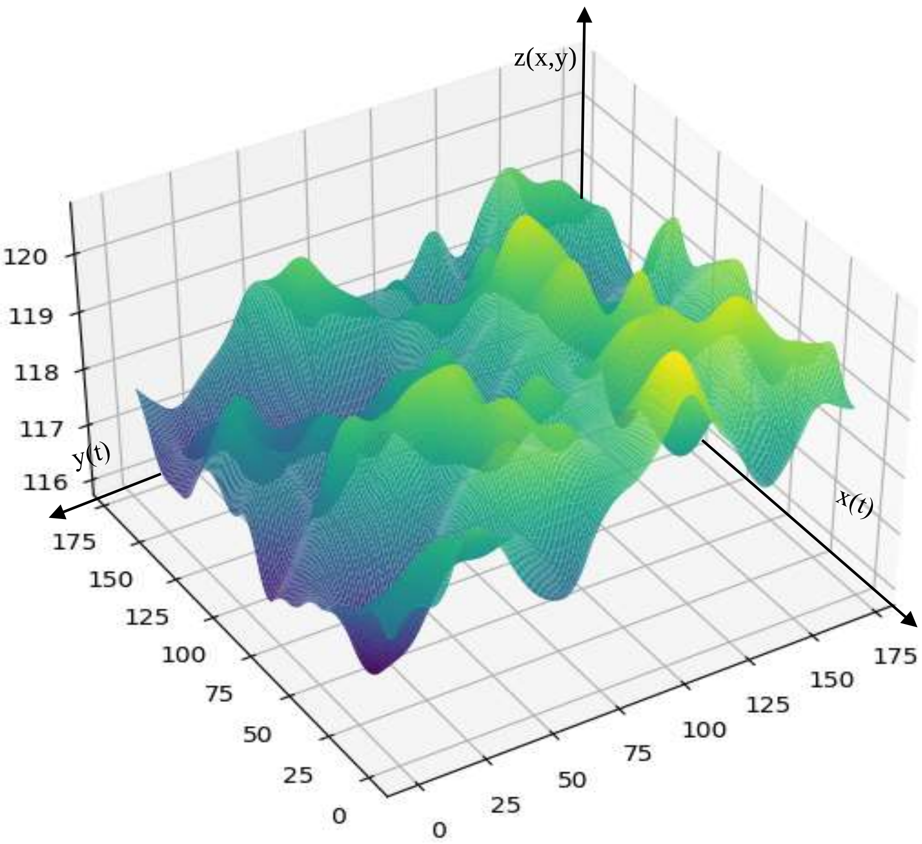

Figure 3. Quadratic B - spline based bivariate signal reconstruction

The graph above illustrates the digital processing of two-variable geophysical signals. The highest peaks on this graph indicate that the amount of radiation is high and that the chemical elements are found in abundance in that location. -0.7 in the table above Δ_1 an absolute mistake. Δ_2-0.59% relative error. As can be seen in the table, the absolute error is high. In order to reduce this error, we will consider building a neural network using B-spline functions and predicting the location of underground radioactive elements with this help.

In a given period, a recurrent network starts from some initial state and evolves until it reaches another state. At this time, training is stopped and the network is reset to its original state, after which the next training period begins. The initial state need not be the same for all periods. It is important that the initial state of each period differs from the final state of the previous one [9; 205] .

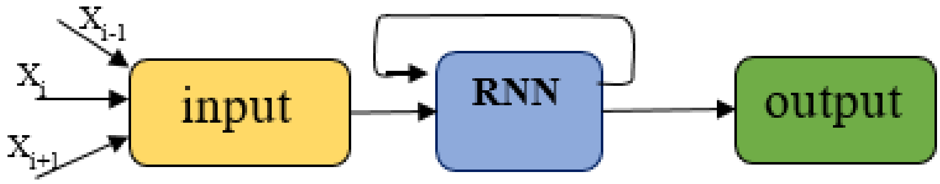

Figure 4. The simplest recurrent neural network architecture

In the above architecture, the RNN block in blue is considered. An iteration algorithm is applied to its input vector and its previous state. In this case, there is no value before the first incoming value x_{i-1}. That’s why we start using the iteration algorithm from the value of the second input x_i [9; 2 07] .

$$h_t = f(h_{t-1}, x_t) \quad (7)$$

h_t is the current state, h_{t-1} is the previous state, x_t is the input state.

$$h_t = \tanh(W_{hh} h_{t-1} + W_{xh} x_t) \quad (8)$$

W_{hh} is the weight in the recurrent neuron, W_{xh} is the weight in the input value of the neuron.

$$y_t = W_{hy,} h_t \quad (9)$$

y_t – output, W_{hy} – output weight. Enter the first value , x_t to the network is given [9; 2 10] .

A B-spline function was proposed as an activation function to improve the accuracy of the neural network. For this, the architecture and algorithm of the recurrent neural network was developed [9; 2 12] .

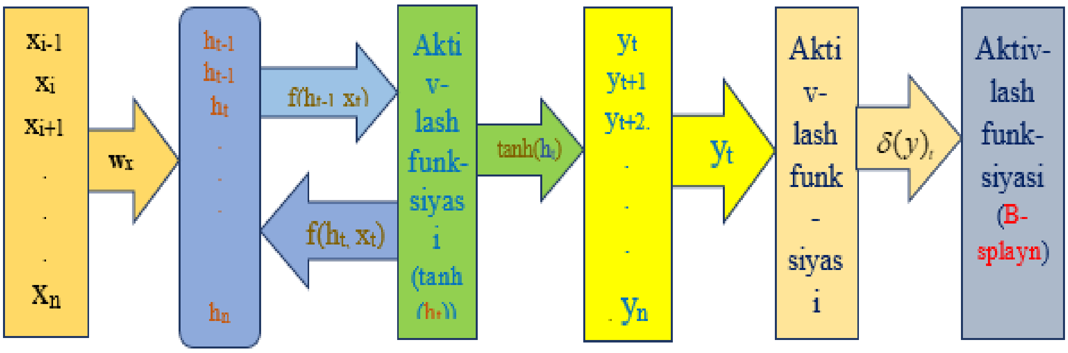

Figure 5. Offer being carried out r ecurrent neural network architecture

The resulting neural network is trained with signals from ore layers in previously mined areas. In this process, the gradients are integrated with the signal received from the surface of the earth in the newly predicted area, and a testing process is carried out to predict the underground ore layer [11; 2 17] .

Two-dimensional radiation signals are reflected in different positions in ore deposits and surface layers. Because, if specific spectral energies of ores are detected in underground layers, there are layers that reflect radiation signals in other layers. Especially if the lead layer is located after the ores, then a very small amount of radiation signal is transmitted to the surface of the earth. In places where there is no lead, it shows more radiation signal [7; 10] . Therefore, large errors occur in the prediction of underground layers by means of radiation signals detected on the surface of the earth. In the proposed architecture, after the softmax activation function, a quadratic B-spline is obtained as the activation function, and the algorithm is as follows.

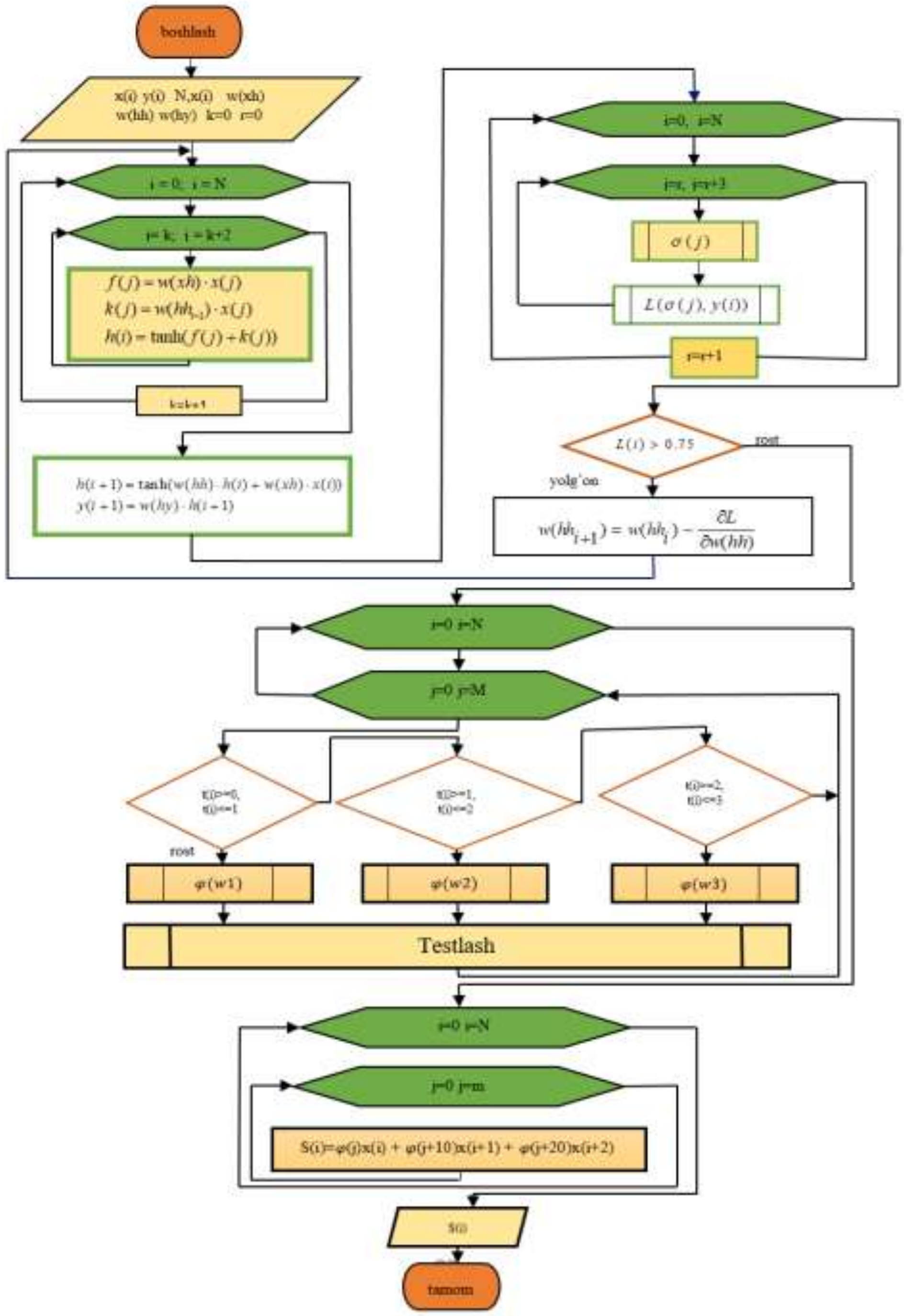

Figure 6. Algorithm block diagram of neural network construction and digital processing of two-dimensional signals

Table 2.

Geophysical signals in recovery absolute and relative errors evaluation

No	$S_i(t)$	NT $S_i(t)$
Δ_1	0.0155	0.00878
Δ_2	3.5%	1.7%

From the results in the table, it can be seen that neural networks built on the basis of B-spline have high accuracy [11; 85] .

Let's consider a mathematical model of building a neural network architecture based on a quadratic B-spline to get a value close to the real value in signal reconstruction. For this we use the following formula:

$$\frac{\partial r_{i,j}}{\partial w_{i,j}} = \frac{2}{N}\sum_{i=0}^{N}\sum_{j=0}^{N}(\varphi(x_{i,j}) - y_{i,j})\cdot\varphi(x_{i,j})'$$
$$\frac{\partial r_{i+1,j+1}}{\partial w_{i+1,j+1}} = \frac{2}{N}\sum_{i=0}^{N}\sum_{j=0}^{N}(\varphi(x_{i+1,j+1}) - y_{i+1,j+1})\cdot\varphi(x_{i+1,j+1})' \qquad (10)$$
$$\frac{\partial r_{i+2,j+2}}{\partial w_{i+2,j+2}} = \frac{2}{N}\sum_{i=0}^{N}\sum_{j=0}^{N}(\varphi(x_{i+2,j+2}) - y_{i+2,j+2})\cdot\varphi(x_{i+2,j+2})'$$

Using the determined gradient values, with the help of signals received over the ground, we will test the detection of ore layers in the unexcavated area of the earth [11; 2 08] .

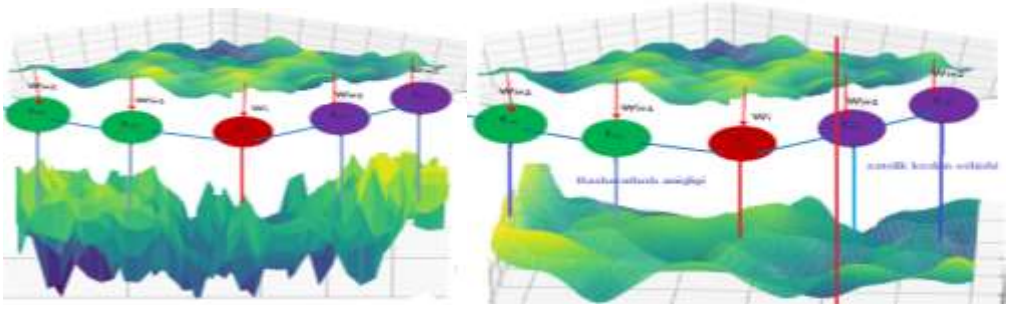

Figure 5. Subsurface layer detection process based on recurrent neural network

Table 3.

Evaluation of absolute and relative errors in two-variable geophysical signal recovery and ore layer prediction

No	S i (t)	NT S i (t)	S i,j (t)	RNN	NT S i,j (t)
Δ_1	0.015	0.0087	0.4110	0.62	0.0 1
Δ_2	3.5%	1.7%	4.3%	5.1%	3.2%
t_1	2.3 ms	2.7 min	6.9 ms	7.3 min	7.5-9 min

CONCLUSION

Today, artificial intelligence methods are entering all fields. The effectiveness of these methods consists in reducing the error to a minimum using the probable values, and using the prediction values to produce the desired results with high accuracy. Therefore, the B-spline function was selected among several activation functions and its use in neural networks was considered. This method shows that it is possible to determine the location and size of useful radioactive ores underground even without drilling. This method can increase the accuracy of software results with real measurement values by up to 20%. It is considered promising that this method can be used in the evaluation of background radiation values depending on the spectral energy and frequency generated on the basis of the ionizing rays coming from underground useful radioactive ores.

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