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# Stability Assessment of an Ore Mill Electric Drive Using Machine Learning

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**Abstract**

The relevance of the study is due to the need to improve electric drive systems operated in harsh conditions. The goal of the study is to create a model for assessing the state of stability of the electric drive of an ore mill using machine learning capabilities, which will provide high performance and the ability to work consistently in different systems. Various sustainability assessment models have been developed based on 6 machine learning algorithms. The study and comparison of models built using artificial neural networks (ANN) of different architectures was carried out using various learning methods. The expediency of using the Tree and ANN algorithms to develop a model for assessing electric drive stability is substantiated. The novelty of the results obtained lies in the fact that the model has high accuracy, high speed, and the ability to detect instability in uncertain operating modes of the electric motor of an electric drive, as well as the possibility of coordinated operation with various systems. The practical value is that the model allows, at an intellectual level, to provide effective control and fault diagnosis of complex electric drive systems, which cannot be achieved using the known methods.

*Keywords:* Machine Learning; Neural Network; Ore Mill; Electric Drive; Intelligent Model Discipline.

## 1. Introduction

The correct organization of technological processes at manufacturing enterprises is mainly due to the smooth operation and efficient operation of electric drive systems that ensure the operation of the technological mechanisms [1–5]. An electric drive system is a complex system operating under load, the mechanical and electrical parts of which are in constant interaction. The electrical part of the system consists of an energy accumulator and a converter connected by an electric and magnetic connection. The mechanical part is an inertial mass connected by elastic mechanical joints [6, 7]. During operation, the elastic links in the mechanical part of the electric drive system are subjected to mechanical shocks, which change with a certain frequency and lead to an increase in the wear rate of the structural components of the system and prevent the stable operation of the system. They are especially undesirable for systems operating with variable loads [8, 9]. Such is the electric drive system that ensures the operation of the ore mill; it is energy-intensive and operated in difficult conditions.

Studies show that ore mills used in various technological processes operate with an arbitrarily varying load [5, 10–12]. The random nature of the load change is due to the qualitative characteristics of the ore, the degree of filling of the crushing drum, and the degree of wear of the lining protecting the walls. The ore grinding mill is mainly started without loading the ore into the mill, which makes it possible to facilitate the operation of the electric drive system to some

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extent. Meanwhile, during operation, flickering occurs in the elastic links of the electric drive system due to the dynamic parameters of the mechanical transmission system and random changes in the torque of resistance created by the mill. Flickering in the mechanical part of the system eventually leads to the wear and deformation of mechanical components, which leads to an emergency or system failure. This leads to a decrease in the efficiency of subsequent processes and unnecessary losses of electricity [13]. Due to an increase in the intensity and amplitude of elastic flickers that occur in the mechanical part of the mill's electric drive system during operation, the system may be in an unstable state, which increases the likelihood of its being in an emergency state.

Considering the above, as well as the fact that the grinding process is the main production stage for obtaining ore concentrate and various building materials [5, 14], an assessment of the stability state aimed at improving the efficiency of its electric drive system is a task of scientific and technical interest. There are various approaches and recommendations aimed at improving the efficiency of the electric drive system of the ore mill. Sapsalev et al. [15] proposed a new approach to ensuring the stability of a two-mass electromechanical system with a magnetic coupling. To linearize the system, a transfer function is obtained between the electromagnetic torque of the motor and the angular velocity of the second mass. The stability of a linearized electromechanical system was considered using the Hurwitz criterion. The results obtained make it possible to analyze transients in linear and nonlinear systems in the MATLAB Simulink environment. To improve the efficiency of the mill, it was proposed to optimize its electric drive system [16]. Two variants of the electric drive system were studied:

- With a low-speed synchronous motor without a gearbox;
- With an asynchronous motor and a gearbox.

The analysis shows that the most energy-efficient system is one with an electric drive without a gearbox and a low-speed synchronous motor, while a smooth start is provided by a system with an asynchronous motor thanks to a hydraulic clutch [16]. Machine learning capabilities have been successfully applied to increase mill productivity and save the electricity consumed by the electric drive [17]. A simulation model was proposed to control the stability of a multistage electric drive system [18]. The results of testing the model show that the proposed control algorithm has the best capabilities for tracking commands, the best protection against interference, and higher performance than a traditional PID regulator. Compared with the traditional mathematical model, the proposed simulation model is closer to real working conditions. This makes it possible to take the non-linear factors into account and solve the problem of inconsistency identified during control [18].

The studies devoted to the development of control technologies for electric drive systems and their application are also of interest [19, 20]. Blagodarov et al. [20] have developed recommendations for developers of electric drive systems based on artificial intelligence. Various approaches to reducing the intensity of fluctuations occurring in the system and improving the accuracy of dynamic positioning are presented. The proposed approaches are applicable to cases where the mechanical system is flexible. A method is proposed for determining the parameters of a model of a two-mass electromechanical system based on oscillograms obtained in operating and emergency modes [21]. The technique is universal and includes the calculation of the moments of inertia of rotating masses, the coefficients of elastic rigidity and vibration damping, as well as the time constants of the motor air gap torque control circuit.

In a number of studies, an attempt has been made to develop intelligent electric drive control systems that prevent possible malfunctions [22–24], which, however, cannot be applied for the comprehensive solution of the problems that arise during the ore crushing process. Baghdasaryan & Avetisyan [25] discussed the issues of the stability of the motion of the "electric motor – technological load" system. It is confirmed that the stability margin can change during the operation of the system by changing the tensile torque. It is shown that a change in the stiffness of the connection of the motion transmission link causes a change in the frequency of flickering of mechanical links, which provides information on the state of the system. This article also presents a stability control algorithm, but it is not recommended to use it in systems with varying loads.

Ren & Qingzhen [26] investigated the dynamic characteristics and stability of a permanent magnet synchronous motor (PMSM). Using the Ruth-Hurwitz criterion, stability conditions and bifurcation conditions for equilibrium points were obtained. It is confirmed that to ensure the stable operation of the motor, its own parameters must be calculated in an area in which there is only one stable equilibrium. Even though the dynamics of PMSM behavior have been studied with and without external load, the proposed model does not consider the operating modes of the motor. In addition, the results obtained only record the conditions for stable operation of the motor and cannot be widely used for solving control and diagnostic problems.

Kodkin et al. [27] present the well-known Popov stability criterion for nonlinear systems based on nonlinear frequency characteristics. It is shown that, in comparison with traditional methods, the proposed method makes it possible to design the structure of the electric drive system more efficiently. The results obtained can be used to determine the stability conditions and develop methods of regulation for tracking electric drives. At the same time, it is important to note that this work does not take into account the influence of the elastic links on stability. The importance of this factor is taken into account in article [28]. In this case, the dynamic stability of the system is assessed for operating modes with sudden steps in supply voltage. It should be noted that, however, the models developed by Kodkin et al. [27] and Kulakovskiy & Aristov [28] do not take into account the dynamics of load changes and also cannot work consistently at the intellectual level.

Ibrahim et al. [29] analyzed the influence of magnetic saturation and rotor position on transient processes and the stability limits of a synchronous reluctance motor. It has been confirmed that magnetic saturation increases the stability limit and torque of a synchronous reluctance motor. On the other hand, changing the q-axis flux linkage has a great impact on motor performance and its stability limits. The analysis carried out does not give a complete picture of the state of stability of a synchronous electric drive since it does not take into account the characteristic parameters of the transmission links.

The analysis shows that some studies are best suited to increase the productivity of the grinding process and decrease energy consumption. Another group of works considers the increase in efficiency of the process from the point of view of researching and evaluating the operating characteristics of the mechanical part of the electric drive system that drives the mechanism. Various approaches have been proposed to control fluctuations occurring in the elastic links of the electric drive system, as well as to prevent their harmful effects using regulators. Undoubtedly, important results have been obtained that are applicable to improving the efficiency of the electric drive system of the ore mill. However, in these studies, information about the state of stability of the system is incomplete since the possibility of providing a synchronous motor in asynchronous modes is not considered. The transients caused by this can make the system unstable, which eventually leads to deformation of the elastic links. Neglecting the stability conditions during transients can lead to an inadequate use of control capabilities. It can be stated that the considered approaches cannot be integrated into the industrial challenges of the 4th generation.

Our research shows that there is significant potential to improve the efficiency of the ore mill. This is due to the development of an intelligent model that comprehensively takes into account the transient phenomena of the electric drive system, evaluates its stability, and is integrated into the control system. The following circumstances serve as the basis for the above:

- Insufficient application of the methods and tools for assessing the stability of the control systems, diagnostics, and monitoring of the electric drive of ore mills;
- The lack of methods that ensure high performance and accuracy in assessing the stability of the system with a random change in load;
- Insufficient use of intelligent solutions to assess the stability of the system;
- Insufficient assessment of the operating modes of the synchronous motor. The use of models that do not take into account the possibility of their operation in asynchronous mode for a certain period of time.

Based on the importance of having accurate information about the stability of the system to improve the efficiency of the ore mill electric drive system, as well as the effectiveness of using intelligent approaches to synthesize a stability assessment model, the purpose of this paper and the tasks to be solved for its implementation are formulated. The aim of the paper **is** to develop a model for assessing the stability of the mechanical part of the mill's electric drive system using machine learning capabilities, which will ensure high productivity and the possibility of coordinated operation in various systems.

The structure of the paper is as follows: Section one presents the status of the issue being considered in the study. The papers of interest for improving the efficiency of the ore mill and its electric drive systems are analyzed. The necessity and purpose of applying a new approach to assessing the instability of the electric drive system of the ore mill are substantiated. Section 2 provides the methodology and algorithm for solving the main tasks for assessing the state of instability of the system. Section 3 presents the results obtained to assess the state of stability using various machine learning methods as well as various neural network architectures and learning algorithms. Section 4 provides comments and recommendations on the results of the study.

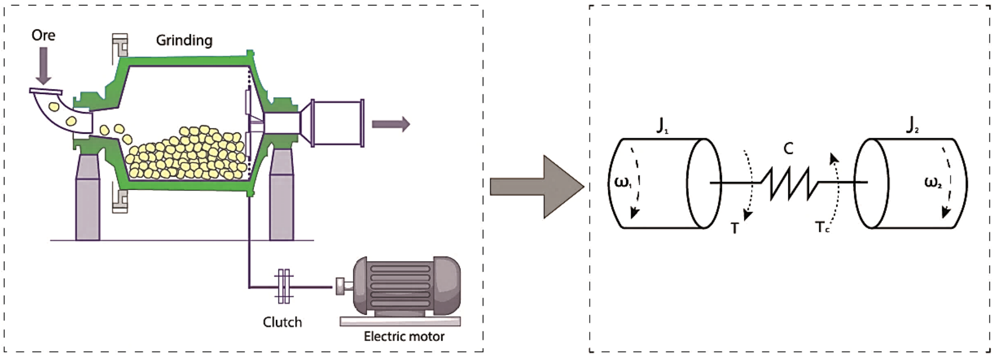
## 2. Material and Methods

Due to its high efficiency and power factor, the synchronous motor has been widely used for crushing ore at production plants [5, 30, 31]. For this reason, stability assessment is carried out for a synchronous electric drive system, the mechanical part of which consists of an ore mill, a synchronous electric drive motor, and a clutch (Figure 1). During operation, the synchronous motor may briefly switch to an asynchronous mode. This differs from the usual mode in that the motor operates with a slip other than zero for a certain time interval [32]. Considering that the asynchronous mode can also be caused by an emergency decrease in the motor supply voltage and an increase in the torque of resistance created by the mill, this circumstance is taken into account when forming the database. To assess the stability of the electric drive system of the ore mill, the fact that the electric drive system can be in three different states is taken into account:

- Unstable;
- Stable without stock;
- Stable with stock.

To assess the stability of the system, 2 types of models are considered, namely:

- Two-state alarm. The output signal of the model indicates a stable or unstable state of the system,
- Three-state alarm. The output signal of the model signals are: an unstable, stable without stock and stable with stock state of the system.




(a) (b)

**Figure 1. The physical model of the electric drive of the ore mill, (a) block diagram, (b) kinematic diagram of the connection between the motor and the ore mill.**

Using the capabilities of machine learning to assess the stability of the electric drive system, the following tasks are solved:

- Database acquisition;
- Assessment of the impact of the database input data on the state of stability;
- Assessment and comparative analysis of the stability of the system using neural networks trained using various architectures and methods;
- Assessment and comparative analysis of the state of the system's stability using various intelligent algorithms used in classification problems;
- Development of recommendations for the use of a model for assessing the state of stability in the control system of an ore mill.

The flowchart of the algorithm for this workflow is presented in Figure 2.

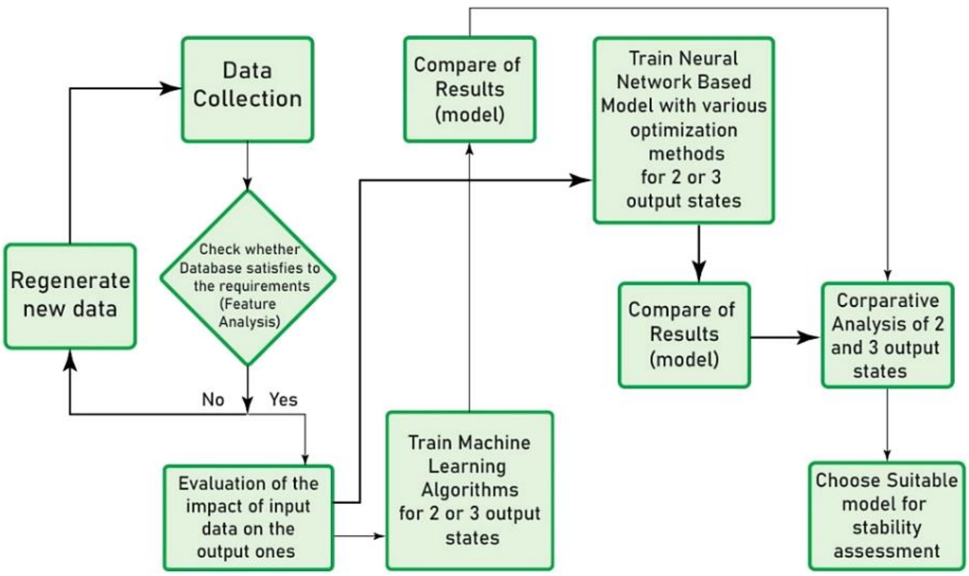



**Figure 2. The flowchart of the algorithm of the workflow**

### 2.1. Creating a Database

To train intelligent model data, you must have a database. To create the base, the stability conditions obtained for the mechanical part of the synchronous electric drive system that ensures the operation of the ore mill were used [33]. Taking into account that the reasons for the occurrence of non-standard operating modes of a synchronous motor in an electric drive and their manifestations are numerous and can disrupt the normal flow of the technological process, under stable conditions, the possibility of the motor appearing in various operating modes is taken into account. Details of the database generation algorithm are described below (Figure 3).

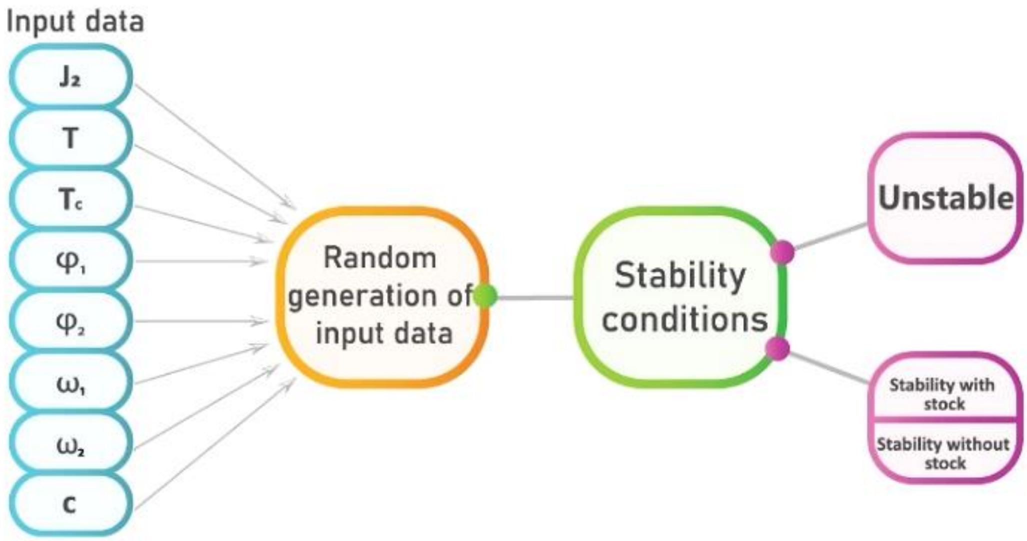



**Figure 3. The block diagram of the database creation**

The boundary values of the input data are entered, with the help of which the database is formed. The input data of the system is randomly generated. The following input data are used: the electromagnetic torque of the motor ($T$), the torque of resistance ($T_c$) created by the ore mill, the displacement angles of the motor shaft and the mill ($\varphi_1, \varphi_2$) and the angular velocities of rotation ($\omega_1, \omega_2$), the moment of inertia of the mill ($J_2$), the stiffness of the connection of the mechanical part ($c$). For stable data, their stability margin is checked. The results are recorded in the database.

To determine the stability conditions, the following differential equation was used to describe the dynamics of the electric drive system with discrete masses.

$$\begin{cases} T - T_{12} = J_1 \frac{d^2\varphi_1}{dt^2} \quad T_{12} - T_c = J_2 \frac{d^2\varphi_2}{dt^2} \\ \frac{dT_{12}}{dt} = c(\omega_1 - \omega_2) \quad T = T_s - T_{as} \end{cases} \tag{1}$$

where $\omega_1 = \frac{d\phi_1}{dt}$;$\omega_2 = \frac{d\phi_2}{dt}$; $J_1$ is the moment of inertia of the rotor of the motor; $T_{12}$ is the elastic torque.

The torque $T$ of the synchronous electric drive motor is represented by synchronous $T_s$ and asynchronous $T_{as}$ components. In the system of Equations 1, the following expression was used to determine the torque of resistance created by the ore mill [34].

$$T_c = m_o + m_1\phi_2 - m_2(\phi_2)^3, \tag{2}$$

where $m_o, m_1, m_2$ are the coefficients.

The stability conditions were obtained on the basis of Lyapunov's stability theory by qualitative study of Equation 1.

A database containing more than 500,000 data has been created, consisting of 8 inputs and one output, which has two or three signal response capabilities.

To improve the efficiency of the database, the impact of the input data on stability conditions is evaluated.

The effects on the output signals of the system of angular displacements of the electric drive motor and mechanism (Figure 4) and speeds (Figure 5), joint stiffness and the moment of inertia of the mill (Figure 6), the influence of the torque of resistance created by the ore mill and the electromagnetic torque of the motor (Figure 7) are studied. The studies were carried out in relative units.

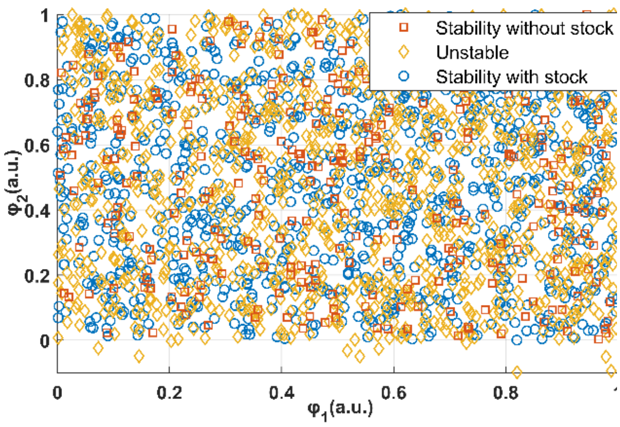



**Figure 4. The influence of the displacement angles of the electric drive motor and the ore mill on the stability of the system.**

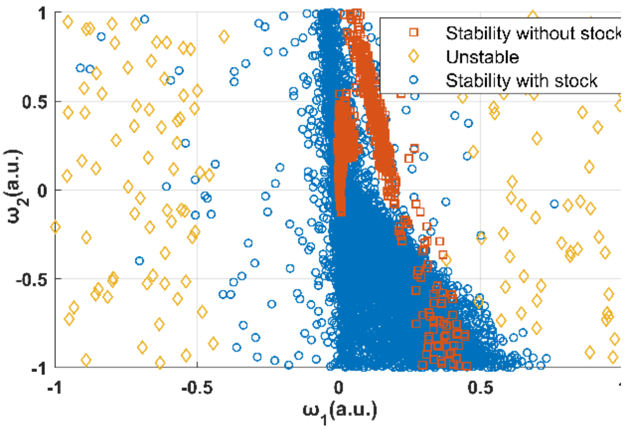



**Figure 5. The influence of the rotation angles of the electric drive motor and the ore mill on the stability of the system.**

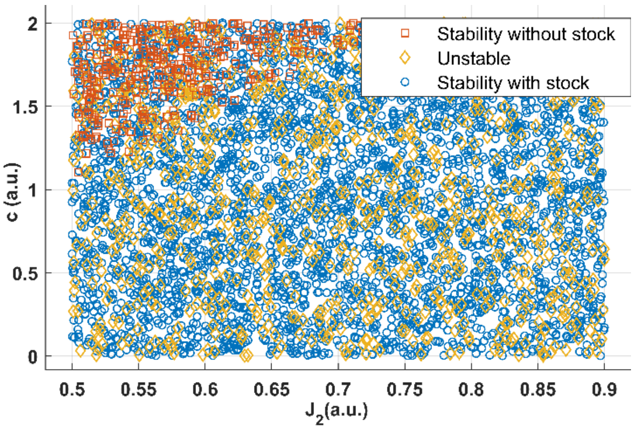



**Figure 6. The effect of bond stiffness and the moment of inertia of the mill on the stability of the system.**

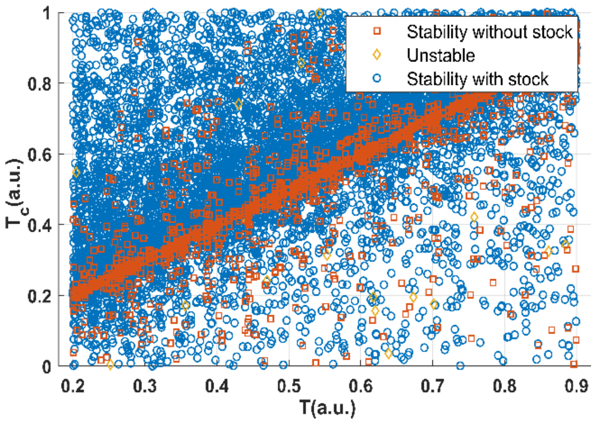



**Figure 7. The influence of the torque of resistance created by the ore mill and the electromagnetic torque of the motor on the stability of the system.**

### 2.2. Methods Used to Synthesize the Stability Assessment Model

To assess the stability of the system, 6 algorithms are considered that are widely used to solve classification problems (Tree, Discriminant, KNN, SVM, Logistic Regression, and Naive Bayes) [35–40], available in the Classification Learner Toolbox environment of the MATLAB software package. At the same time, the possibilities of using an artificial neural network with different architectures and learning algorithms are considered.

## 3. Results and Discussion

Based on the described method, tests were carried out on the electric drive system of a drum mill type 2700×3600mm used in the production of ore concentration. Table 1 shows the data of the ore mill and the electric drive motor.

**Table 1. Data of the system under test**

| **Model (D×L)** | 2700 × 3600 (mm) | **Motor power** | 380 (kW) |
|---|---|---|---|
| **Rotation speed of cylinder** | 20.7 (r/min) | **Rotation speed** | 187.0 (r/min) |
| **Useful power** | 328 (kW) | **The flywheel torque of the rotor** | 9.0 (t $m^2$) |
| **Loading of ball** | 26 (t) | **coefficient of efficiency** | 88.4 (%) |

### 3.1. Results of the Application of Machine Learning Algorithms

To develop a model for assessing the stability of the mill's electric drive system, the database created using the algorithms shown in Figure 3 is considered for signaling two and three states, respectively (Tables 2 and 3). To assess the effectiveness of the model, the characteristics of speed and accuracy, as well as the memory capacity, are considered.

The results show that the models developed using Discriminant, Linear SVM, Efficient Linear SVM, Naive Bayes, Efficient Logistic Regression algorithms have a rather low (less than 82.02%) accuracy. The accuracy of the models developed using the KNN and Tree algorithms exceeds 90% (Figures 9 and 11). At the same time, the accuracy of models signaling two states running on CNN and Tree algorithms is higher and approaching 100% (Figure 11). The KNN algorithm, which showed the highest accuracy, has a longer learning time and a lower prediction speed than the Tree algorithm (Figures 8, 10). In addition, the memory size of the model with the Tree algorithm is small. Of the considered options, the worst parameters of prediction speed, occupied volume, and training time are provided by the model developed on the basis of a discriminant algorithm, whose accuracy does not exceed 56.57 (Figure 11).

**Table 2. Characteristic parameters of the model signaling instability, stability with a stock and stability without a stock for various algorithms**

| Algorithm | Model Type | Prediction speed (obs/sec) | Model size (Mb) | Training tine (sec) | Accuracy (%) |
|---|---|---|---|---|---|
| Tree | Fine Tree | 1236000 | 0.031 | 7.47 | 96.9531 |
| | Medium Tree | 1344100 | 0.009 | 6 | 94.2069 |
| | Coarse Tree | 2106000 | 0.006 | 4.3 | 92.5609 |
| Discriminant | Linear Discriminant | 1404700 | 0.007 | 3.85 | 50.41 |
| | Quadratic Discriminant | 1200000 | 0.009 | 4.5 | 50.4 |
| K-Nearest Neighbors (KNN) | Fine KNN | 112450 | 59.94 | 11.55 | 99.9018 |
| | Medium KNN | 46603 | 59.94 | 20.6 | 99.9018 |
| | Cosine KNN | 1187.9 | 46.94 | 436.7 | 99.9017 |
| | Cubic KNN | 28455 | 59.94 | 32.4 | 99.9017 |
| | Weighted KNN | 47311 | 59.94 | 34.86 | 99.9017 |
| | Coarse KNN | 8704 | 59.944 | 68.5 | 80.6553 |
| Support Vector Machines (SVM) | Efficient Linear SVM | 806020 | 0.039 | 36.3 | 64.0386 |
| | Linear SVM | 357510 | 0.019 | 25446.8 | 59.4517 |
| | SVM Kernel | 30511 | 0.810 | 454.7 | 94.2961 |
| Logistic Regression | Logistic Regression Kernel | 29435 | 0.810 | 213.6 | 91.1817 |
| | Efficient Logistic Regression | 598470 | 0.039 | 39.6 | 64.0381 |
| Naive Bayes | Gaussian Naive Bayes | 812910 | 0.009 | 9.4 | 30.8886 |

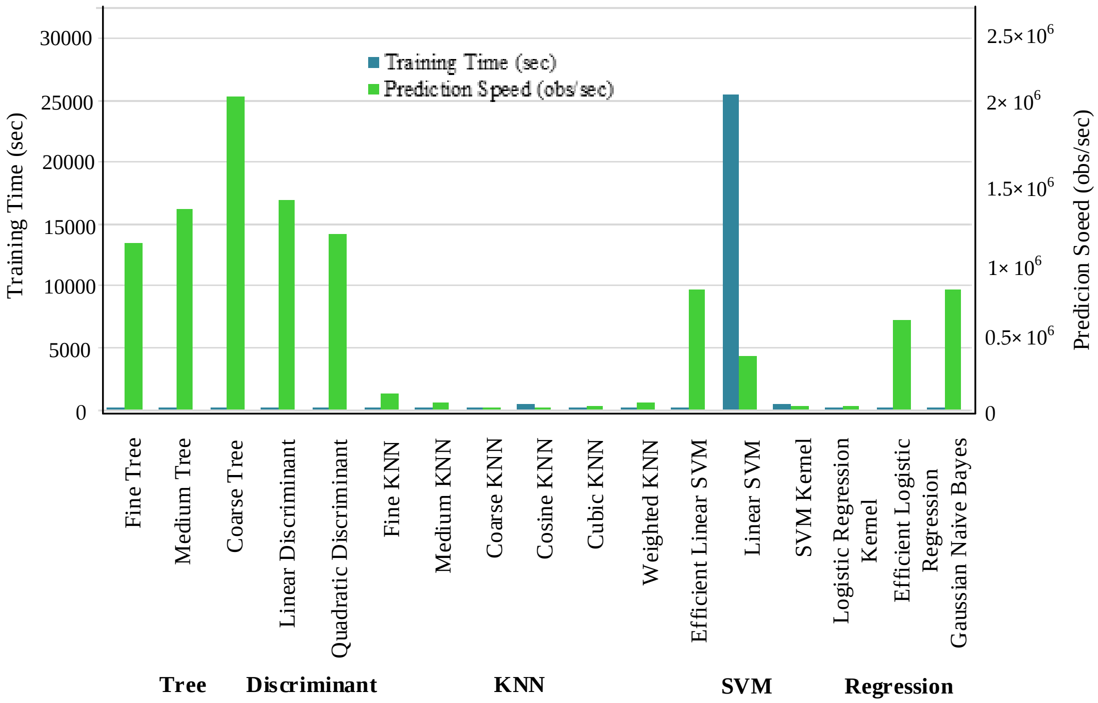



**Figure 8. The learning time of the model signaling instability, with and without a stock of stability, as well as the prediction speed for various machine learning algorithms**

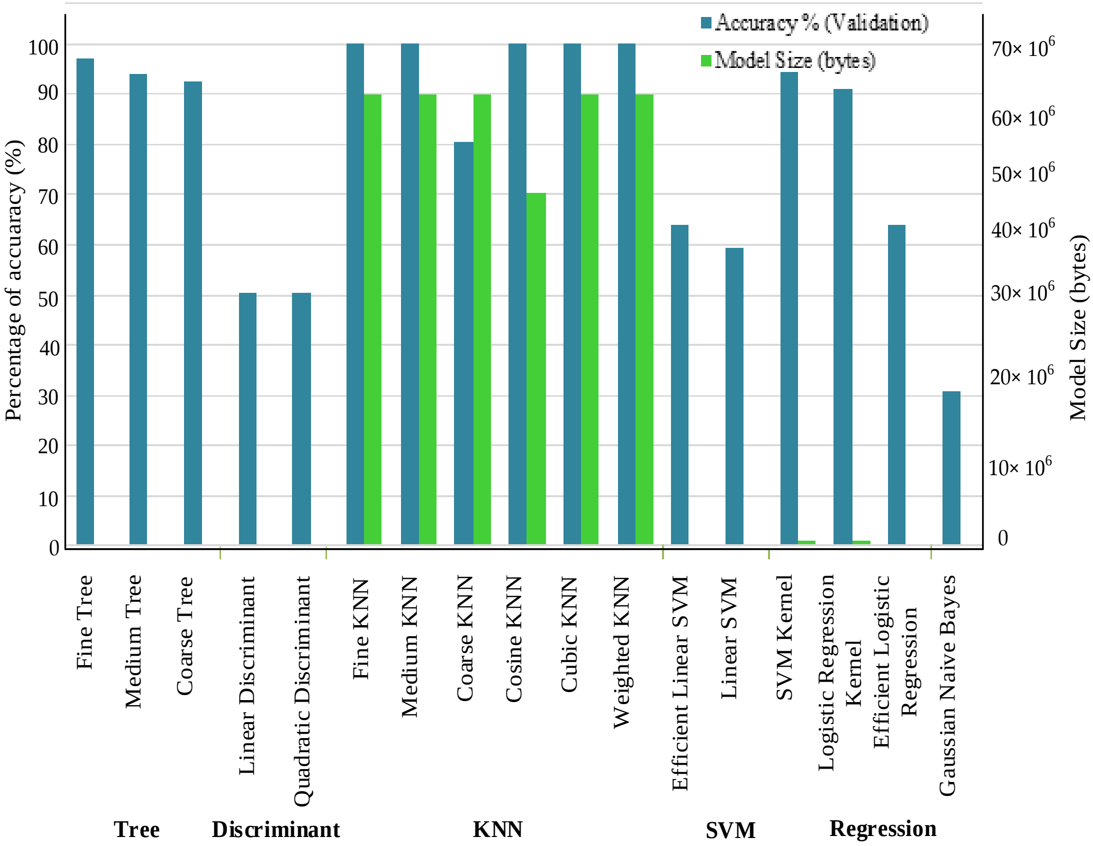



**Figure 9. Accuracy and volume of the model signaling instability, stability with and without a stock for various machine learning algorithms**

**Table 3. Characteristic parameters of the model signaling instability and stability for various algorithms**

| Algorithm | Model Type | Prediction speed (obs/sec) | Model size (Mb) | Training tine (sec) | Accuracy (%) |
|---|---|---|---|---|---|
| Tree | Fine Tree | 795930 | 0.02808 | 12.05 | 99.75 |
| | Medium Tree | 1023000 | 0.00875 | 10.8 | 99.37 |
| | Coarse Tree | 1067700 | 0.00516 | 9.83 | 97.71 |
| Discriminant | Linear Discriminant | 1150200 | 0.00634 | 4.08 | 56.57 |
| | Quadratic Discriminant | 1296900 | 0.00739 | 2.53 | 56.57 |
| K-Nearest Neighbors (KNN) | Fine KNN | 144560 | 61.2471 | 6050 | 100 |
| | Medium KNN | 41702 | 61.2471 | 6078 | 100 |
| | Cosine KNN | 931 | 61.2471 | 6680 | 100 |
| | Cubic KNN | 25148 | 48.1393 | 6082 | 100 |
| | Weighted KNN | 45558 | 61.2471 | 6100 | 100 |
| | Coarse KNN | 6466 | 61.2471 | 6110 | 83.19 |
| Support Vector Machines (SVM) | Efficient Linear SVM | 1381800 | 0.0117 | 18.1 | 70.05 |
| | Linear SVM | 914 | 40.880 | 13329 | 56.57 |
| | SVM Kernel | 56054 | 0.0129 | 6292 | 82.02 |
| Logistic Regression | Logistic Regression Kernel | 52290 | 0.0129 | 6220 | 75.6 |
| | Efficient Logistic Regression | 1166400 | 0.0118 | 3.9 | 70.05 |
| Naive Bayes | Gaussian Naive Bayes | 758700 | 0.0071 | 7.45 | 56.57 |

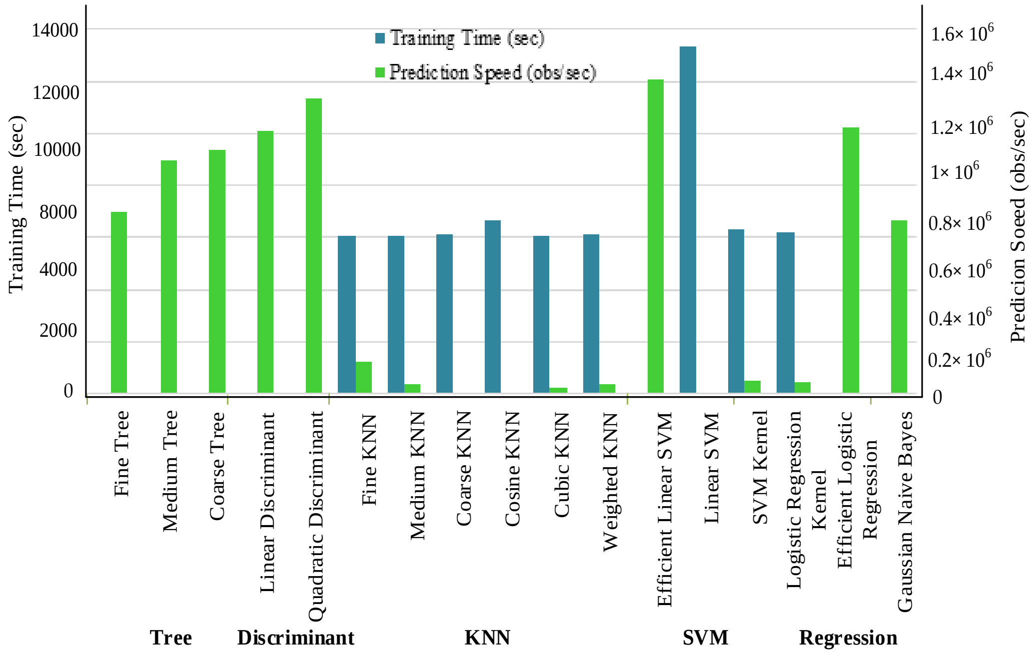



**Figure 10. Training time and prediction speed of the model signaling instability and stability for various machine learning algorithms**

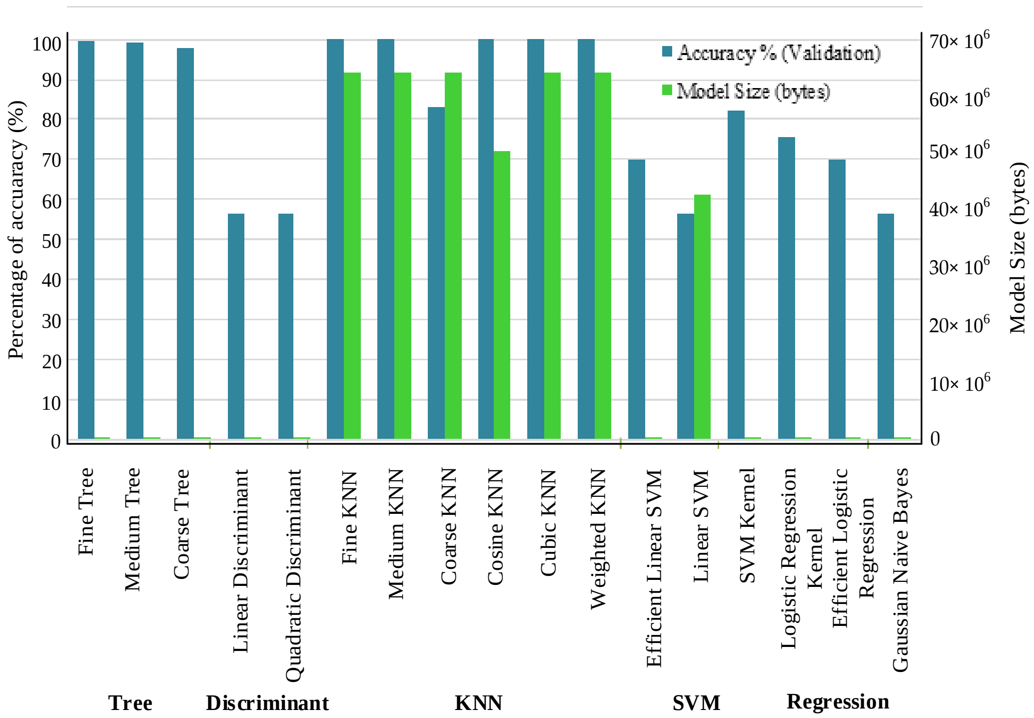



**Figure 11. Accuracy and volume of the model signaling instability and stability for various machine learning algorithms**

### 3.2. Results Obtained Using an Artificial Neural Network

There are no clear rules for choosing the architecture, training method, and activation function of an artificial neural network [41–43]. For this reason, to synthesize a model for assessing the state of system stability, models with different architectures, activation functions, and learning algorithms that are used in them are studied. Considering this, two types of classification are used: Binary Classification (signaling about instability and stability) and Multi-Class classification (signaling about instability, stability with a stock, and stability without a stock); therefore, the activation function on the output layer is selected based on the conditions of the problem. In the case of Binary Classification, the activation function at the output level is Sigmoid, and in the case of Multi-Class Classification, it is SoftMax. Selected activation functions in hidden layers are shown in the table.

After choosing the architecture of the neural network, the weighting coefficients that minimize the error are determined. Various optimization algorithms can be used for this purpose. Bearing in mind that the learning algorithm has different parameters and settings, in order to properly control them, it is necessary to understand the impact of the optimization method used on the system's performance. A neural network model for assessing the stability of the electric drive system of an ore mill was considered for 9 different architectures and 5 different gradient optimization methods used for training [44, 45] (Tables 4 and 5).

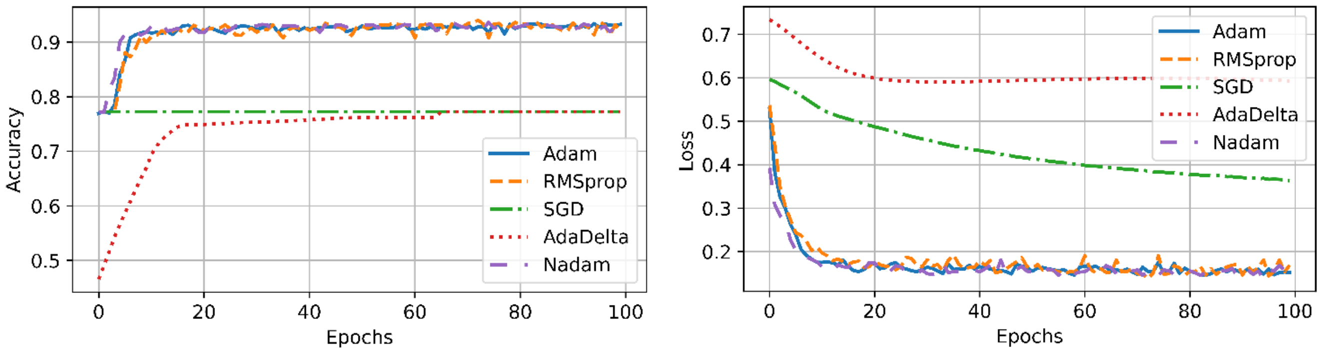
From the results obtained, it is clear that the use of an artificial neural network for signaling three states of stability does not give the desired results for solving this problem (Table 4). The study of the created database shows that the data on stability without reserve makes up only 9.2% of the database, which reduces the accuracy and increases the training time. The use of a neural network in the instability and stability signaling model increases the accuracy and reduces the training time (Table 5). At the same time, it is noteworthy that with the same architecture, the accuracy of the model with the activation function and the duration of training are significantly influenced by the training method. Dependencies characterizing the effectiveness of gradient optimization methods Adam, RMSprop, SGD, AdaDelta, and Nadam are shown in Figures 12 to 18.

**Table 4. Characteristic parameters of the model signaling instability, stability with and without a stock, created on the basis of neural networks of various architectures**

| Optimization method | Neurons in the first hidden layer | Neurons in the second hidden layer | Prediction speed (obs/s) | | Model size (Mb) | | Training time (sec) | | Accuracy (%) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Sigmoid | ReLU | Sigmoid | ReLU | Sigmoid | ReLU | Sigmoid | ReLU |
| Adam | 10 | - | 29.47 | | 0.025 | | 90.92 | | 58.0 | |
| RMSprop | | | 29.43 | | 0.021 | | 88.29 | | 57.6 | |
| SGD | | | 29.84 | | 0.021 | | 88.52 | | 53.4 | |
| AdaDelta | | | 29.83 | | 0.025 | | 89.60 | | 51.8 | |
| Nadam | | | 29.49 | | 0.025 | | 94.47 | | 57.6 | |
| Adam | 20 | - | 29.74 | 29.61 | 0.026 | 0.026 | 93.26 | 90.72 | 57.7 | 59.8 |
| RMSprop | | | 29.59 | 29.95 | 0.022 | 0.022 | 89.64 | 88.37 | 53.4 | 60.3 |
| SGD | | | 29.85 | 29.71 | 0.022 | 0.022 | 88.48 | 86.80 | 51.3 | 55.4 |
| AdaDelta | | | 29.87 | 29.91 | 0.026 | 0.026 | 91.55 | 89.63 | 57.8 | 53.1 |
| Nadam | | | 29.64 | 30.23 | 0.026 | 0.026 | 94.29 | 93.17 | 57.9 | 60.8 |
| Adam | 30 | - | 29.67 | | 0.028 | | 95.03 | | 57.8 | |
| RMSprop | | | 29.68 | | 0.022 | | 92.54 | | 58.0 | |
| SGD | | | 26.25 | | 0.022 | | 95.21 | | 53.5 | |
| AdaDelta | | | 29.89 | | 0.028 | | 97.97 | | 51.8 | |
| Nadam | | | 26.74 | | 0.028 | | 99.62 | | 57.9 | |
| Adam | 20 | 10 | 28.50 | | 0.034 | | 103.93 | | 59.2 | |
| RMSprop | | | 28.80 | | 0.027 | | 107.05 | | 58.3 | |
| SGD | | | 29.29 | | 0.027 | | 103.98 | | 51.8 | |
| AdaDelta | | | 26.24 | | 0.034 | | 102.54 | | 52 | |
| Nadam | | | 26.89 | | 0.034 | | 115.88 | | 59.3 | |
| Adam | 30 | 20 | 29.58 | 29.56 | 0.041 | 0.041 | 99.82 | 100.1 | 59.4 | 61.0 |
| RMSprop | | | 29.85 | 29.87 | 0.031 | 0.031 | 97.28 | 94.0 | 58.9 | 55.6 |
| SGD | | | 29.75 | 28.96 | 0.031 | 0.031 | 95.26 | 92.19 | 51.9 | 54.4 |
| AdaDelta | | | 29.56 | 29.89 | 0.041 | 0.041 | 99.99 | 95.84 | 51.9 | 61.4 |
| Nadam | | | 29.83 | 29.84 | 0.041 | 0.041 | 105.2 | 100.9 | 59.1 | 61.9 |
| Adam | 10 | 5 | 28.84 | 29.64 | 0.032 | 0.032 | 98.34 | 96.61 | 58.9 | 60.3 |
| RMSprop | | | 30.18 | 28.44 | 0.025 | 0.025 | 93.0 | 94.00 | 57.7 | 60.2 |
| SGD | | | 31.38 | 27.18 | 0.025 | 0.025 | 90.89 | 92.33 | 51.5 | 55.0 |
| AdaDelta | | | 30.02 | 29.31 | 0.032 | 0.032 | 95.14 | 95.28 | 51.7 | 50.0 |
| Nadam | | | 30.57 | 29.80 | 0.032 | 0.032 | 99.67 | 98.61 | 58.2 | 59.7 |

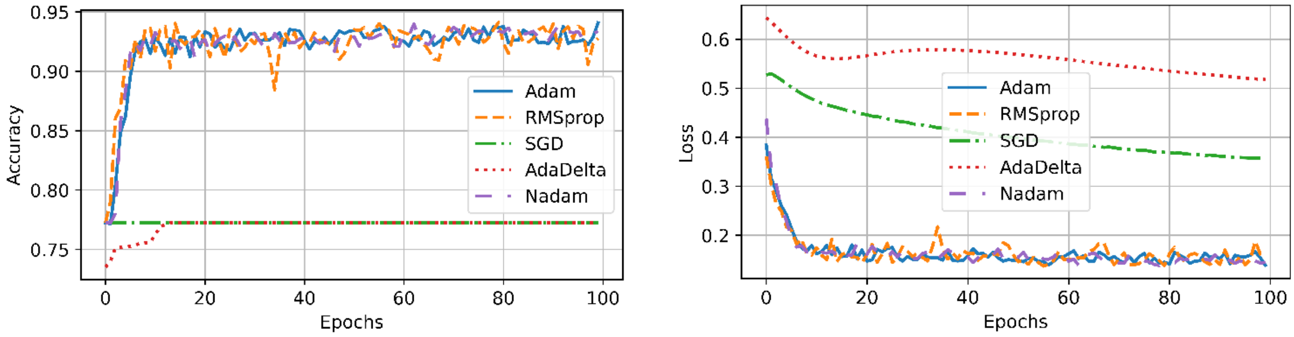
**Table 5. The characteristic parameters of the model signaling instability and stability, created on the basis of neural networks of various architectures**

| Optimization method | Neurons in the first hidden layer | Neurons in the second hidden layer | Prediction speed (obs/s) | | Model size (Mb) | | Training time (sec) | | Accuracy (%) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Sigmoid | ReLU | Sigmoid | ReLU | Sigmoid | ReLU | Sigmoid | ReLU |
| Adam | 10 | - | 24.77 | | 0.024 | | 75.65 | | 93.2 | |
| RMSprop | | | 25.82 | | 0.020 | | 70.80 | | 93.1 | |
| SGD | | | 25.38 | | 0.020 | | 70.75 | | 77.2 | |
| AdaDelta | | | 24.72 | | 0.024 | | 73.57 | | 77.2 | |
| Nadam | | | 24.74 | | 0.024 | | 77.59 | | 93.1 | |
| Adam | 20 | - | 24.91 | 25.18 | 0.026 | 0.027 | 78.47 | 72.26 | 93.2 | 92.2 |
| RMSprop | | | 25.71 | 25.73 | 0.020 | 0.021 | 72.64 | 73.72 | 92.5 | 92.6 |
| SGD | | | 25.01 | 25.84 | 0.020 | 0.021 | 72.67 | 68.99 | 77.2 | 85.3 |
| AdaDelta | | | 21.83 | 26.00 | 0.026 | 0.027 | 75.16 | 72.03 | 77.2 | 75.8 |
| Nadam | | | 26.08 | 19.72 | 0.026 | 0.027 | 78.72 | 79.76 | 96.7 | 93.3 |
| Adam | 30 | - | 25.41 | | 0.029 | | 75.38 | | 92.3 | |
| RMSprop | | | 25.21 | | 0.023 | | 73.68 | | 93.3 | |
| SGD | | | 25.66 | | 0.023 | | 70.84 | | 77.2 | |
| AdaDelta | | | 24.94 | | 0.029 | | 79.47 | | 77.2 | |
| Nadam | | | 25.01 | | 0.029 | | 78.32 | | 92.3 | |
| Adam | 20 | 10 | 26.52 | | 0.034 | | 78.68 | | 93.3 | |
| RMSprop | | | 25.21 | | 0.027 | | 77.76 | | 91.7 | |
| SGD | | | 24.96 | | 0.027 | | 79.51 | | 77.2 | |
| AdaDelta | | | 25.07 | | 0.034 | | 78.65 | | 77.2 | |
| Nadam | | | 25.65 | | 0.034 | | 82.53 | | 93.8 | |
| Adam | 30 | 20 | 25.23 | 24.25 | 0.042 | 0.042 | 84.26 | 79.43 | 93.27 | 94.4 |
| RMSprop | | | 25.20 | 25.23 | 0.032 | 0.032 | 80.07 | 77.54 | 93.36 | 92.3 |
| SGD | | | 25.72 | 25.73 | 0.032 | 0.032 | 82.93 | 74.44 | 77.24 | 87.9 |
| AdaDelta | | | 25.35 | 25.43 | 0.042 | 0.042 | 81.76 | 76.84 | 77.24 | 76.3 |
| Nadam | | | 24.99 | 25.87 | 0.042 | 0.042 | 85.27 | 81.13 | 93.59 | 93.2 |
| Adam | 10 | 5 | 25.95 | 20.88 | 0.031 | 0.030 | 75.15 | 77.52 | 92.6 | 93.7 |
| RMSprop | | | 26.64 | 25.09 | 0.025 | 0.025 | 74.58 | 77.44 | 92.3 | 93.8 |
| SGD | | | 26.66 | 25.69 | 0.025 | 0.025 | 71.33 | 72.22 | 77.2 | 84.9 |
| AdaDelta | | | 26.54 | 23.75 | 0.031 | 0.030 | 74.51 | 74.86 | 77.2 | 75.1 |
| Nadam | | | 26.43 | 25.96 | 0.031 | 0.030 | 78.86 | 78.86 | 92.9 | 93.0 |



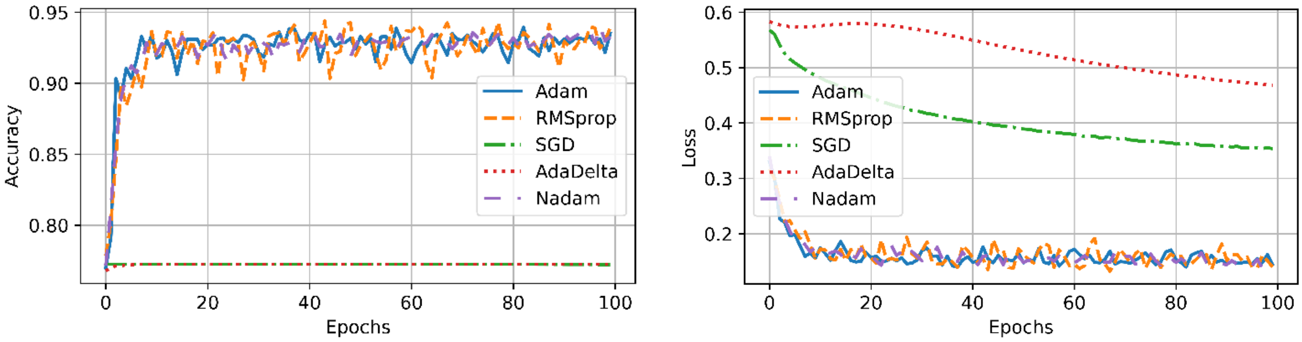

(a) (b)

**Figure 12. Dependences on Epochs of (a) training accuracy and (b) losses of a neural model with the Sigmoid activation function with one hidden layer of 10 neurons in the case of various optimization methods**



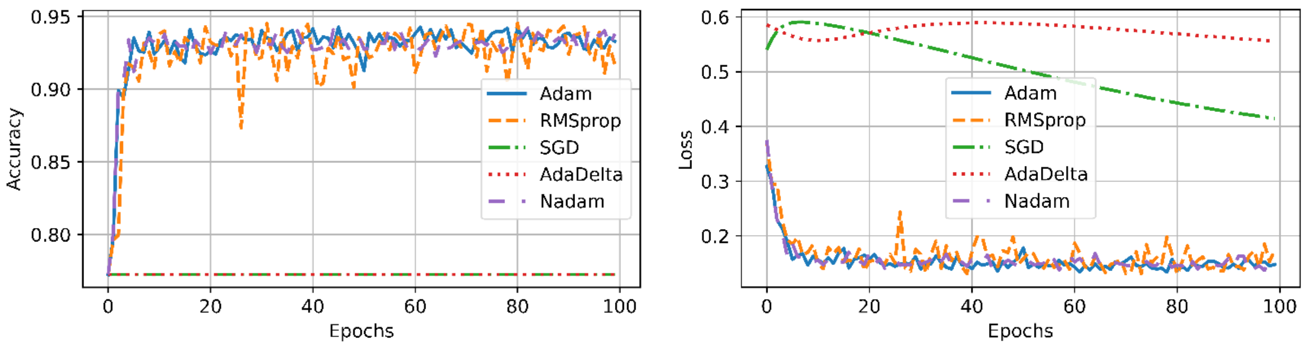

(a) (b)

**Figure 13. Dependences on Epochs of (a) training accuracy and (b) losses of a neural model with the Sigmoid activation function with one hidden layer of 20 neurons in the case of various optimization methods**



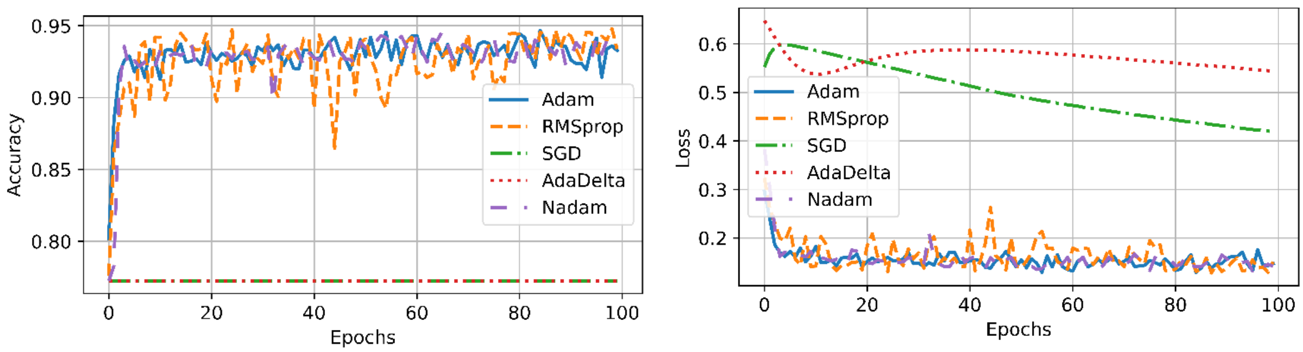

(a) (b)

**Figure 14. Dependences on Epochs of (a) training accuracy and (b) losses of a neural model with the Sigmoid activation function with one hidden layer of 30 neurons in the case of various optimization methods**



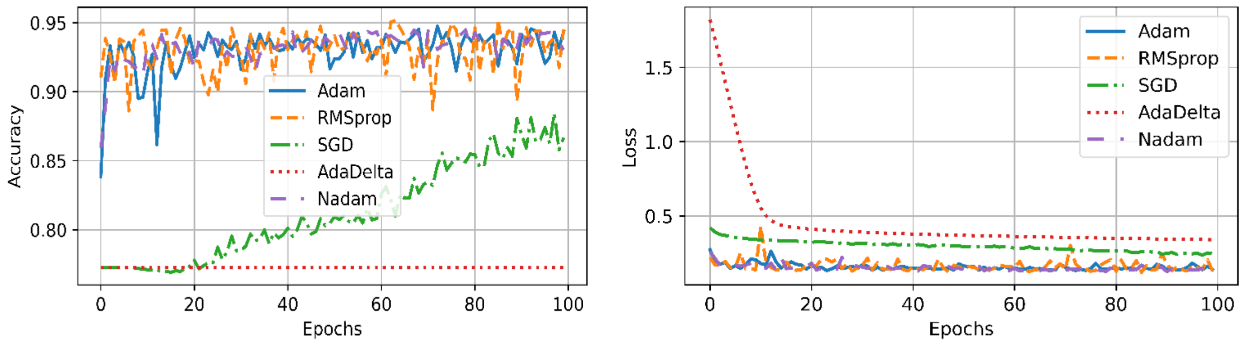

(a) (b)

**Figure 15. Dependences on Epochs of (a) training accuracy and (b) losses of a neural model with the Sigmoid activation function with two hidden layers of 20 and 10 neurons in the case of different optimization methods**



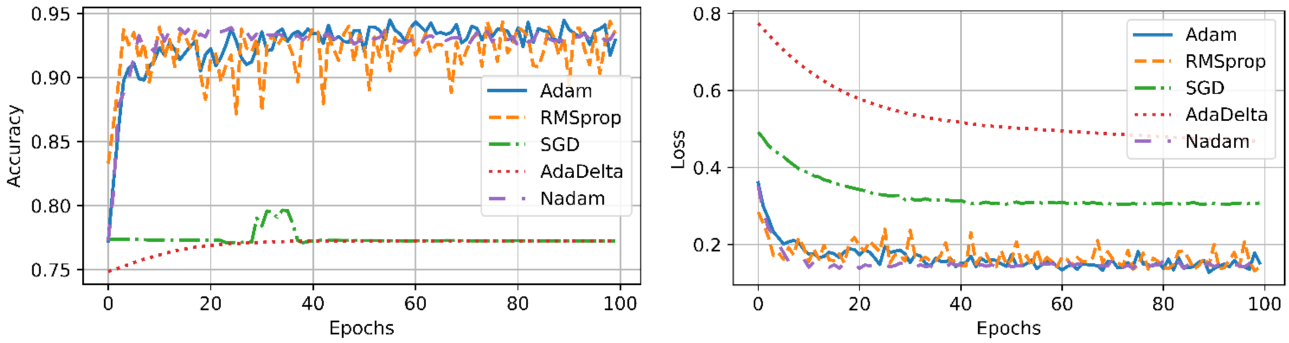

(a) (b)

**Figure 16. Dependences on Epochs of (a) training accuracy and (b) losses of a neural model with the Sigmoid activation function with two hidden layers of 30 and 20 neurons in the case of different optimization methods**




(a) (b)

**Figure 17. Dependences on Epochs of (a) training accuracy and (b) losses of a neural model with the ReLU activation function with two hidden layers of 30 and 20 neurons in the case of different optimization methods**



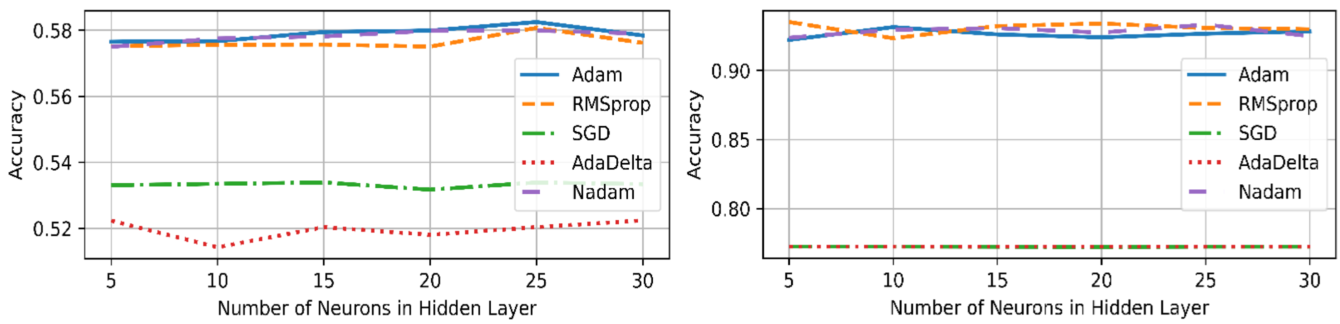

(a) (b)

**Figure 18. Dependences on Epochs of (a) training accuracy and (b) losses of a neural model with a ReLU activation function with two hidden layers of 10 and 5 neurons in the case of different optimization methods**

From the above results, it can be seen that the use of AdaDelta and SGD optimization methods in this network training problem in the case of 100 epochs can provide a maximum of 77, 24%, and 87.9%, respectively. The highest accuracy can be achieved by using the Nadam method to train a network with a structure of 20 neurons in one hidden layer with a sigmoid activation function. In this case, the maximum accuracy of 96.65% is recorded starting from the 70th epoch. As a result of application in various structures, the lowest accuracy was 85.27%.

For the studied neural network architectures, fairly stable performance is provided by the Adam and RMSprop optimization methods, the accuracy of which ranges from 9.7 to 94.4%. Training time, prediction speed, and the size of the models considered do not undergo drastic changes, unlike machine learning algorithms (Tables 4 and 5).

The number of neurons in the hidden layer has no significant impact on the accuracy of the model (Figure 19). The maximum change is recorded for RMSprop optimization methods, which does not exceed 1.7%.




(a) (b)

**Figure 19. Dependences of Validation and Accuracy on the number of neurons in the hidden layer (a) for the signaling model of three stability states, (b) for the signaling model of two stability states**

## 3.3. Discussion

The analysis shows that an intelligent model for assessing the stability of the electric drive system of an ore mill can be synthesized both on the basis of the Tree algorithm and on the basis of an artificial neural network. In this case, the stability assessment model using the Tree algorithm can be used to control and monitor the electric drive system. Its use for automated control purposes is not recommended because it is ineffective for sorting or grouping operations. Models with two-state signaling created on the basis of an artificial neural network can be successfully used in automated control systems for the electric drive of an ore mill, as well as monitoring and diagnostics. This statement is supported by the fact that the ore mill electric drive system operates under uncertain conditions due to random load changes and changes in synchronous motor operating conditions. A serious alternative to digital control of electric drive systems operating in such conditions is fuzzy logic and the introduction of neural network control systems. These intelligent systems can be successfully integrated with a neural network stability assessment model and provide high system performance. In addition, these neural network models can be built into real controllers and work consistently in the control system, which cannot be said about the model with the Tree algorithm.

From the analysis of the results obtained it follows that:

- All the input parameters used to develop the ore mill electric drive system model significantly influence the stability state. In the database created for training purposes, data without a stability stock does not exceed 9.1%. This allows to state that, depending on the requirements of the problem being solved, stability assessment models with signaling of two or three states can be used in practice:
    - Signaling of states of instability and stability;
    - Signaling of states of instability, stability with and without stock.
- The use of developed models using well-known machine learning algorithms (Discriminant, Linear SVM, Efficient Linear SVM, Naive Bayes, and Efficient Logistic Regression) to improve the efficiency of the ore mill electric drive is not guaranteed due to its insufficient characteristic parameters.
- The developed models using the KNN and Tree algorithms provide high accuracy in signaling both two and three states. However, their accuracy in three-state signaling models is slightly reduced. In models based on the KNN algorithm, this decrease ranges from 0.1 to 3.1, which is due to the fact that the method is "trained" only on new data without taking into account previous experience.
- The use of neural models with three-state signaling, regardless of the architecture and training algorithm, is impractical due to their low accuracy (maximum 61.9%). This is explained by the fact that the neural network is poorly trained due to the paucity of stock data.
- The Nadam, RMSprop, and Adam algorithms provide the lowest losses and highest accuracy in training a neural network model. The worst indicators are shown by the AdaDelta and SGD algorithms.
- As a result of taking into account the possibilities of operating a synchronous motor in asynchronous mode for a certain period of time, it became possible to increase the reliability of the developed model.
- The best result from the models created based on the neural network registers a variant with 20 neurons in one hidden layer with a Sigmoid activation function with two-state signaling.

In this study, we proposed a new hypothesis to develop an intelligent stability assessment model for the electric drive system of an ore mill. Application of the obtained results to solve the problems of control, monitoring, and diagnostics of the ore grinding process will ensure high reliability and performance of the system, helping to improve the technical and economic indicators of the product.

## 4. Conclusions

When conducting this research, problems with data collection were overcome. These problems were solved using the model we created, which takes into account all the characteristic parameters of a synchronous electric drive operating with a randomly varying load as well as the possibility of a synchronous motor operating in an asynchronous mode. The degree of influence of a large number of parameters on the state of stability is considered. As a result of the study, 8 characteristic factors were identified. The next difficulty was the impossibility of collecting a large amount of data for stability states without stock, concerning which the authors have drawn a conclusion. The possibilities of machine learning for a comprehensive assessment of the stability of synchronous electric drive systems with dynamic loads have not been used by other authors; therefore, there is no preliminary information on the preferred algorithm and method. For this reason, the authors conducted the research through the study and comparative analysis of a large number of algorithms and optimization methods. The conducted research and analysis can become the basis for the creation of high-performance intelligent systems for control, fault detection, and monitoring of electric drives for various purposes.

Despite the fact that various intelligent electric drives and diagnostic systems are used in practice, they lack the capabilities for a comprehensive assessment of the state of stability that would work in concert with them. For this reason, we proposed a new approach to assess the stability states of the electric drives of ore mills, which are widely used in industry and operate under hard conditions.

As a result of the research conducted with the aim of applying intelligent models for automated control, diagnostics, and monitoring of mineral processing and the production of various building materials, the following conclusions were drawn:

- The existing opportunities and challenges for improving the efficiency and reliability of the ore mill were presented.
- Opportunities have been created for a comprehensive assessment of the stability conditions of the synchronous electric drive of the ore mill. This was done by taking into account the fact that a synchronous motor can be in different operating modes and by taking into account non-linear changes in the torque of resistance created by the mill.
- It has been recorded that the prediction speed, learning time, memory capacity, and accuracy of learning stability assessment models developed on the basis of Tree, KNN, Discriminant, Linear SVM, Efficient Linear SVM, Naive Bayes, Efficient Logistic Regression machine learning algorithms undergo significant changes in cases with three- and two-state signaling. The only exceptions are the accuracy of the Tree and KNN algorithms, whose maximum changes are insignificant and amount to 5.3% and 3.1%, respectively.
- It was registered that in order to develop a high-performance neural network model for assessing stability, it is necessary that its architecture, activation function, and learning algorithm be selected in a consistent manner.
- The analysis of the base formed for training the electric drive system of the ore mill shows that the probability that the system may be in stability mode without stock is small, up to 9.2%.
- To ensure efficient and reliable operation of the control system, diagnostics, and monitoring of the electric drive of the ore mill, it is most advisable to use the following models with two-state signaling:
    - A model based on the Tree algorithm;
    - A neural network model with the Nadam learning algorithm, a sigmoid activation function, and one hidden layer with 20 neurons.
- The results obtained and the proposed intelligent models can be successfully applied to improve the efficiency and reliability of the ore mill, which is widely used in the ore processing and production of building materials, thereby contributing to the improvement of quality and economic indicators of products.

## 5. Declarations

### 5.1. Author Contributions

Conceptualization, M.B. and V.H.; methodology, M.B.; software, V.H.; validation, M.B. and V.H.; formal analysis, V.H.; investigation, M.B.; resources, M.B.; data curation, M.B.; writing—original draft preparation, M.B. and V.H.; writing—review and editing, M.B. and V.H.; visualization, M.B. and V.H.; supervision, M.B.; project administration, M.B.; funding acquisition, M.B. All authors have read and agreed to the published version of the manuscript.

### 5.2. Data Availability Statement

The datasets supporting the conclusions of this article are included in the article.

### 5.3. Funding

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### 5.4. Institutional Review Board Statement

Not applicable.

### 5.5. Informed Consent Statement

Not applicable.

### 5.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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