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MONITORING SYSTEMS IN MINING

Deep Learning and Internet of Things (IoT) Based Monitoring System for Miners

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Abstract—In this study, a miner monitoring system is designed using the Deep Learning (DL) approach and the IoT technology together. It is aimed to determine the area where the miners are located while a possible accident occurs by the proposed system. Experiments were carried out to analyze the effectiveness of the proposed system and the performance evaluations were made. The best result was obtained with an accuracy rate of 97.14%. This rate indicates that the designed miner monitoring system can be used effectively in practice.

Keywords: Internet of Things (IoT), miner monitoring, artificial neural networks, deep learning, LSTM model.

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INTRODUCTION

The mining industry is a high-accident-risk area that requires knowledge, experience, uninterrupted attention, and periodic control. In particular, underground mining is among the working areas that involve high risk in issues related to the health and safety of the miners. The risk of death is higher in accidents occurred in underground mining when compared to the other mining activities [1, 2]. In underground mining, where the human labor force is mainly used, the increasing rate of occupational accidents reveals that prevention systems and emergency plans are crucial. It is very important to take preventive and rescuing precautions in underground mining by taking advantage of constantly developing technologies. There are several studies in which miner monitoring systems have been developed using different methods in the literature [3–5].

The accuracy rate of indoor environment measurements decreases and even the receiving power of the monitoring center may be completely cut off in some areas when using Global Positioning System (GPS) based systems for indoor monitoring. Therefore, Internet of Things (IoT) technology is widely used in location tracking studies for monitoring the indoor environments.

The concept of the Internet of Things can be expressed in the most general sense as systems that allow communication between interrelated computing devices without any need for a person in the field of Information Technology [6]. IoT is closely related to areas such as Radio-Frequency Identification (RFID) technology, wireless sensor networks, or machine-to-machine communication [5]. Applications can be developed in a wide range of areas by processing information obtained from devices on a network established with IoT systems. For example, by monitoring a system, it can be possible to notice adverse situations that may occur in that system in advance, or to minimize damage that may emerge when the adverse situation occurs due to the fact that the location or final state of objects in the system is known. Due to this aspect, IoT systems stand out as a useful technology that can be used in preventing occupational accidents in the field of mining. In recent years, the use of IoT technology have increased significantly in order to take measures against adverse situations that may occur in the underground mining field [6–8].

Artificial neural networks (ANNs) are successfully applied to solve important problems in many areas such as finance, meteorology, earth science, health, and mining. The use of the ANN approach in the mining field is of great interest to researchers [9–13]. In addition, there are studies in which ANN and IoT approaches are used together [14–16]. In recent years, the deep learning approach which is a type of multilayer neural networks has been preferred due to their high success potential in studies carried out with big data. The deep learning model to be applied varies depending on the problem that is addressed.

In this study, a system will be designed using the IoT technology and deep learning in order to determine the location of the miner rapidly when an accident occurred in a mine. It is aimed to present a beneficial system to be used for search and rescue efforts in mine accident cases. For the developed system, an IoT network will be established that allows RSSI (Received Signal Strength Indication) data, which will be sent from the transmitter circuit on the miner, to be read by reference receivers placed in the mine. The distance between the miner and the nearest reference receiver will be calculated using the location formula given in [17] with the RSSI data obtained while monitoring the miners. However, when the environment changes, the calculated distance is affected adversely, and it becomes a necessity to change the environment's coefficient in the location formula manually to reduce this affect. In order to avoid this situation, a Long-Short Term Memory (LSTM) model, which is a deep learning technique will be utilized to automatically estimate the environment coefficient k. A dataset including measured RSSI values, environment's coefficients, and calculated distances will be obtained to be used in the proposed LSTM model. Eventually, after the dataset is applied to the LSTM model, the optimal environment coefficient k will be determined.

1. LITERATURE REVIEW

The development of electronic devices and wireless communication technologies enable the development of new methods for the safety of underground mines and the management of mining enterprises. In the light of these developments, underground monitoring applications have become mandatory for underground mining processes. In [18], the authors have conducted a review study about underground mine positioning technologies.

Monitoring the indoor environments can be achieved by using the sensor devices with wireless sensor network installed in the mine [19, 20]. Technologies such as radio-frequency identification (RFID), ultra-wideband (UWB), inertial navigation system (INS) are used to monitor the miner's location [21, 22]. Besides, IoT technology is also widely used for monitoring the indoor environments. In their study, Ikeda et al. have used the IoT structure to be able to establish an effective communication environment in a mine. They have developed an application that allowed environmental monitoring and location tracking of miners with a wireless sensor network set up in the underground [7].

Excavation process in underground mines leads to various wastes. Accidents may occur due to the necessity of waste disposal which leads to taking some measures. In their study, Sun et al. have proposed a solution in which they used the IoT technology for the waste dam that allowed the evacuation of wastes. They have proposed a real-time waste dam monitoring and pre-alarm system based on the IoT and cloud computing (CC) [8]. Against the methane gas threat in the underground mines, Sikora et al. have used local linear models and the ARIMA model. Air processes in the mine were observed and possible increases in methane gas level were monitored by the proposed system [9]. Ghiasi et al. have aimed the explosion in open pit mines to do the least damage to the emerging mine. They have used the multiple regression and ANN to estimate the explosion models so that the mineral fragments formed as a result of the explosion would be in the form of large crushed rocks and not broken into very small pieces [10]. In their study, Temeng et al. have focused on the safety of the working environment against the environmental threats caused by air over-pressure (AOp) occurring as a result of explosions in the mines. Brain-Inspired Emotional Neural Network (BI-ENN) method was used to estimate the severity level of the waves that would occur before an explosion [11].

In their study, Lin et al. have proposed a combined approach utilizing the ANN and rock fracture criteria to estimate the horizontal main voltage magnitudes by using drilling output data [12]. In their previous study, they had developed a machine learning model to predict maximum horizontal stress based on breakout data [13]. However, due to the limitation in the experimental data, they had experienced difficulty achieving a sufficient minimum horizontal voltage. To overcome this challenge, the ANN model and the Mogi-Coulomb rock fracture criterion approaches were used to predict horizontal stress magnitudes and the average error rate was obtained as 6.82%.

Ozyurt and Karadoğan have studied the applicability of ANN and Game Theory in the selection of underground mining methods. Safety conditions were prioritized for the underground mine while building their model. Six different ANN models were developed based on the physical condition of the underground mine, rock mass properties, environmental factors, and ventilation conditions to determine the suitable mining method [14].

Predicting the possible disasters in advance for the underground mines can also be achieved by monitoring seismic data. For such predictions, evaluations can be made using deep learning techniques in order to draw meaningful results on sensitive data. In this context, Convolutional Neural Networks (CNN) are used to determine the location of micro-seismic events in underground mines [23–25].

In addition to IoT technology, various ANN models such as Long Short Term Memory (LSTM), Deep Belief Network (DBN), and Artificial Hydrocarbon Networks (AHN) were used to solve different engineering problems [15, 16, 26, 27]. In the field of mining, there are also studies in which artificial neural networks and IoT technology are applied together. Li et al. have proposed a method based on the IoT technology and ANN consisting of three layers: detection layer, network layer, and application layer in order to detect failures that may occur in mine crane equipment [28]. Dong et al. have gathered data using IoT technology by setting up sensor networks for waste dams, which are vital for maintaining operation in mining enterprises, and they have proposed a real-time monitoring system over the collected data. Installation of a pre-alarm system was carried out with the generalized regression neural network (GM-GRNN) and the grey model built on the cloud platform. In this way, the safety of waste dams in the mine area was ensured [29]. In their study, Jo and Khan have realized an application on the Azure Machine Learning (AML) Studio platform to monitor air quality and predict pollutant factors in underground coal mines [30]. In this study, an IoT network with Arduino-based sensor modules was installed, and Multilayer Perception–Artificial Neural Network (MLP–ANN) method was used for the predictions on the AML platform.

Table 1 presents an analysis of the studies conducted in the field of mining by using IoT, ANN, and IoT+ANN methods. Publication years of the studies, the scope of the studies in the field of mining, and the methods used in the studies are given in the table. It has been observed that IoT technology is frequently used in studies related to miner monitoring systems in the literature. In addition, it has been determined that various ANN models and systems that are used by combining these models with IoT technology have been used effectively in the field of mining in recent years. However, for the best of our knowledge, any study in which ANN and the IoT are used together for miner monitoring systems has not been encountered yet in the literature. Hence, the aim of this study is to propose a miner monitoring system by using the deep learning approach, which is a multilayer ANN model, and the IoT technology together.

Table 1. Mining related studies in which IoT/ANN/ANN+IoT approaches were used

Year and reference	Scope	Method
2016 [3]	Underground personnel tracking location algorithm	IoT
2016 [4]	A smart sensor and tracking system for underground mining	IoT
2019 [7]	Environmental monitoring, worker location tracking, supervision, and underground wireless communication system	IoT, Wi-Fi Ad Hoc Communication System
2012 [8]	Dam safety, a tailings dam monitoring and pre-alarm system (TDMPAS)	IoT and cloud computing (CC)
2016 [10]	Prediction of the amount of boulder produced in blasting operations at open pit mine	Multiple regression method and ANN
2020 [11]	Prediction of air overpressure	Brain Inspired Emotional Neural Network (BI-ENN)
2020 [12]	Estimation of horizontal principal stress magnitudes from borehole breakout data	ANN and Mogi-Coulomb approach
2020 [14]	Development of an underground mining method and selection model	ANNs and Game Theory
2018 [23]	Micro-seismic event detection and location in underground mines	Convolutional Neural Networks and Deep Learning Techniques
2021 [24]	Detection and location of microseismic events and velocity model inversion from microseismic data acquired by DAS data	Deep Neural Networks
2020 [25]	Automated microseismic detection in downhole distributed acoustic sensing data	Convolutional Neural Networks
2018 [28]	Development of a diagnostics method for mining crane equipment	Self-Organizing Maps (SOM) Neural Network and IoT
2017 [29]	Development of a real-time pre-alarm system for the safety of waste dams	Generalized Regression Neural Network (GRNN) and IoT
2018 [30]	Monitoring underground mine air quality and prediction of pollutant factors	Multilayer Neural Network and IoT

2. MATERIALS AND METHODS

Internet of Things (IoT). IoT technology allows electronic devices to be controlled by connecting to a network. In this way, this type of devices can be controlled with information obtained from sensors connected to electronic devices. The IoT technology is used in many fields such as energy, health, transportation, and agriculture. In addition, this technology is also used in object tracking and alerting systems [31]. GPS systems which calculate the position of objects via satellites are preferred due to their ease of application and high accuracy results in indoor positioning systems. On the other hand, these systems may not be suitable due to the fact that they can lead to problems in indoor location tracking because of possible disconnections in communication with the satellite. Therefore, systems designed with GPS often face with difficulties for effective indoor positioning. Cost-effective and small IoT devices using wireless protocols aim to solve these challenges [32].

Received Signal Strength Indication (RSSI). The RSSI value which indicates the strength of the signal received from IoT devices is used in systems designed for indoor location tracking. In these systems, location of objects is estimated based on the received signal strength changes depending on the signal propagation distance [33]. RSSI signal values are expressed with very small values in dB (decibel). The dB is the ratio between two powers, whereas the dBm is a decibel measurement of the absolute power level. In this study, RSSI values obtained from 3 different environments, outdoor, indoor and underground, are expressed in dBm. The following equation [17] is used to calculate the location of a miner:

$$r = 1 + \left(\frac{-P_r - k - P_0}{20} \right)^{10}, \tag{1}$$

where P_r is the RSSI value obtained from the transmitting device on the miner, dBm; k is the environment coefficient; P_0 is the device error, dBm. The coefficient of environment k and the device error P_0 values are experimentally determined.

Deep learning. It is a multi-layered structure ANN, one of the machine learning methods that provides successful results in areas, such as image processing, speech recognition, and natural language processing. It is used to obtain meaningful inferences from the data.

There are various applications developed using deep learning and IoT technology together. Deep learning approach is often used in studies related to IoT in which analyze data obtained from sensor nodes, predict, and find relationships between data. LSTM is a deep learning model that is frequently used to estimate data in time series for IoT based applications [27, 34].

Figure 1 shows the structures of a simple neural network and a deep neural network. A simple neural network can be designed with three layers: the input layer, the hidden layer, and the output layer. Information is received from the input layer and transferred to the output through the hidden layer. Complex artificial neural networks that have more hidden layers are used for estimation and classification problems with big data. This kind of ANN structures that contains more than three layers is called Deep Neural Networks, and the training process of these networks is called Deep Learning. In this study, it is aimed to develop a monitoring system for tracking a miner with the data obtained from wireless sensor nodes over time. The environment coefficient k in equation (1) that is used for determining the location of a miner must be changed manually. To overcome this situation, an LSTM model which automatically determines the environment coefficient is proposed.

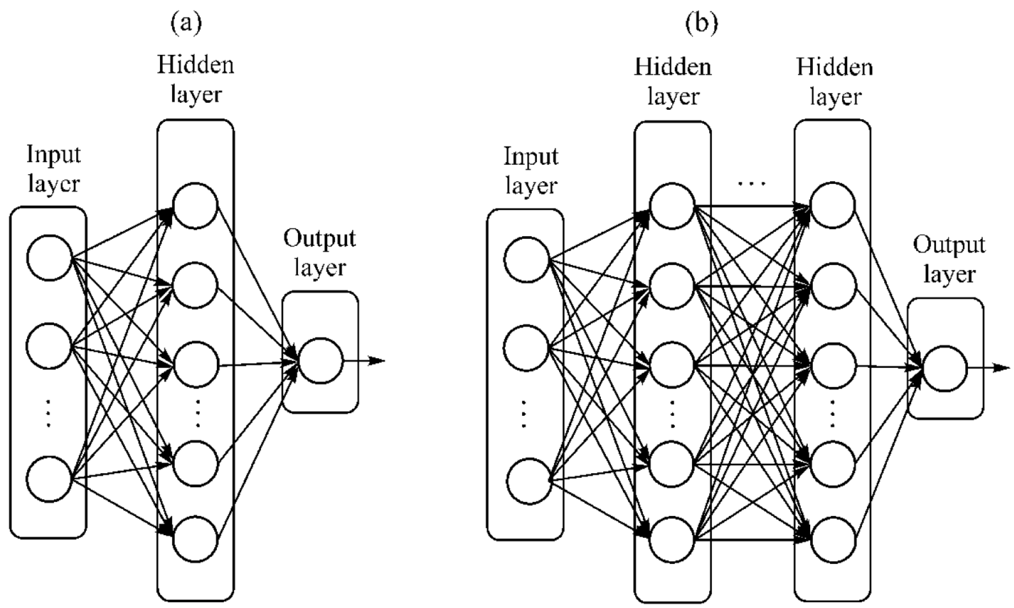

Fig. 1. Structures of (a) Simple Neural Network and (b) Deep Neural Network.

Long-Short Term Memory (LSTM). Recurrent neural networks (RNNs) are used to process data received by time series or in sequence. A time series is a collection of data that is in a state of constant change depending on time and sorted by time. In RNNs, a loop structure is created by applying forward and feedback operations and in this way, the output is obtained from past data. However, when a large amount of past data is needed, situations, such as the decrease and disappear of derivative or increase of it to very high values, occurs during the feedback process. For this reason, training of RNNs becomes difficult when a large amount of time series is required. Because of this disadvantage, the LSTM structure has been developed [35]. The LSTM structure contains an input layer, output layer, and a forget layer that does not take part in the RNN structure [36]. There is a gate structure to remove the previous data, that is not desired to be processed, from memory. With the help of this gate, it is determined which data will be stored in memory. The structure of the LSTM model is given in Fig. 2. Basically, it consists of three gates: forget, input, and output.

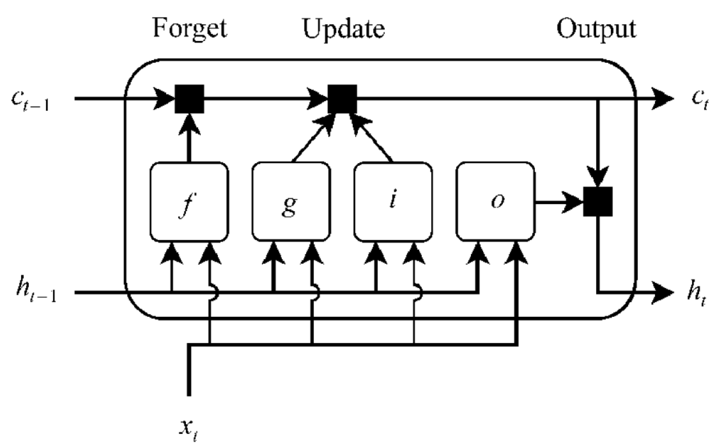

Fig. 2. LSTM Structure.

In this LSTM structure x_t shows the flow of x time series through the LSTM layer, while h_t and c_t show the output and the cell state at step t, respectively, f refers to the forget gate, g is the cell candidate, i, o are the input and output gates, respectively. The function of the forget gate, the first gate in the LSTM architecture, is to determine the information to be deleted from the memory cells. It specifies what amount of information contained in the c_{t-1} memory cell at the previous moment will pass into the c cell [21]. It is governed by the following equation:

$$f_t = \sigma_g (W_f x_t + R_f h_{t-1} + b_f),$$

where W is the learning weight matrix; R refers to the recurrent weights; b is the state of deviation; σ is the logistical sigmoid function used as the threshold function for neural networks.

The input gate determines how much new information can be entered into the memory cell at that moment:

$$i_t = \sigma_g (W_i x_t + R_i h_{t-1} + b_i)$$

and then can be entered into the output gate:

$$o_t = \sigma_g (W_o x_t + R_o h_{t-1} + b_o) .$$

The value of g denotes the cell candidate:

$$g_t = \sigma_g (W_g x_t + R_g h_{t-1} + b_g) .$$

In this LSTM model, to obtain the optimum value of the environment coefficient k, three input neurons are used: environment type (indoor/outdoor/underground), calculated distance and actual distance.

Dataset. In this study, an experimental miner monitoring system to collect data was set up including the transmitter device carried by the miner working in the underground mine, reference receiver, and central receiver. In order to physically model a mine environment, RSSI values were measured in three different areas (indoor area, underground parking lot, and outdoor area) defined as "environment" in the dataset. The number of gallery, transmitter, and reference receiver may vary depending on the environment.

The dataset is created over the following designed system:

—stationary reference receivers connected to a monitoring center;

—each miner has a transmitter that broadcasts an RSSI signal;

—reference receivers send these RSSI signals broadcasted from transmitters to the monitoring center;

—the distance between the miner and the nearest reference receiver is calculated using equation (1).

During each measurement, the dataset engages such parameters as the unique ID for each measurement, the experimental environment, the environment coefficient k, the device error P_0, actual and calculated distance, and the error difference. Table 2 shows an example part of the created dataset.

Table 2. An example part of the created dataset

ID	Environ ment	k	P_0	Distance, cm		Error difference, cm
				actual	calculated	
1	1	22	25	150	151	1
2	1	22	25	150	170	20
3	1	22	25	150	144	–6
4	1	22	25	200	170	–30
67	2	19	23	150	150	0
68	2	19	23	150	156	6
69	2	19	23	150	154	4
70	2	19	23	200	189	–11
132	3	18	23	150	131	–19
133	3	18	23	150	128	–22
134	3	18	23	150	150	0
135	3	18	23	200	200	0

The complete data set includes the values of distances over a total of 225 measurements at different distances and environments, including 76 in the outdoor, 84 in the indoor, and 65 in the underground. The comparison of the actual and calculated distances are given in Fig. 3.

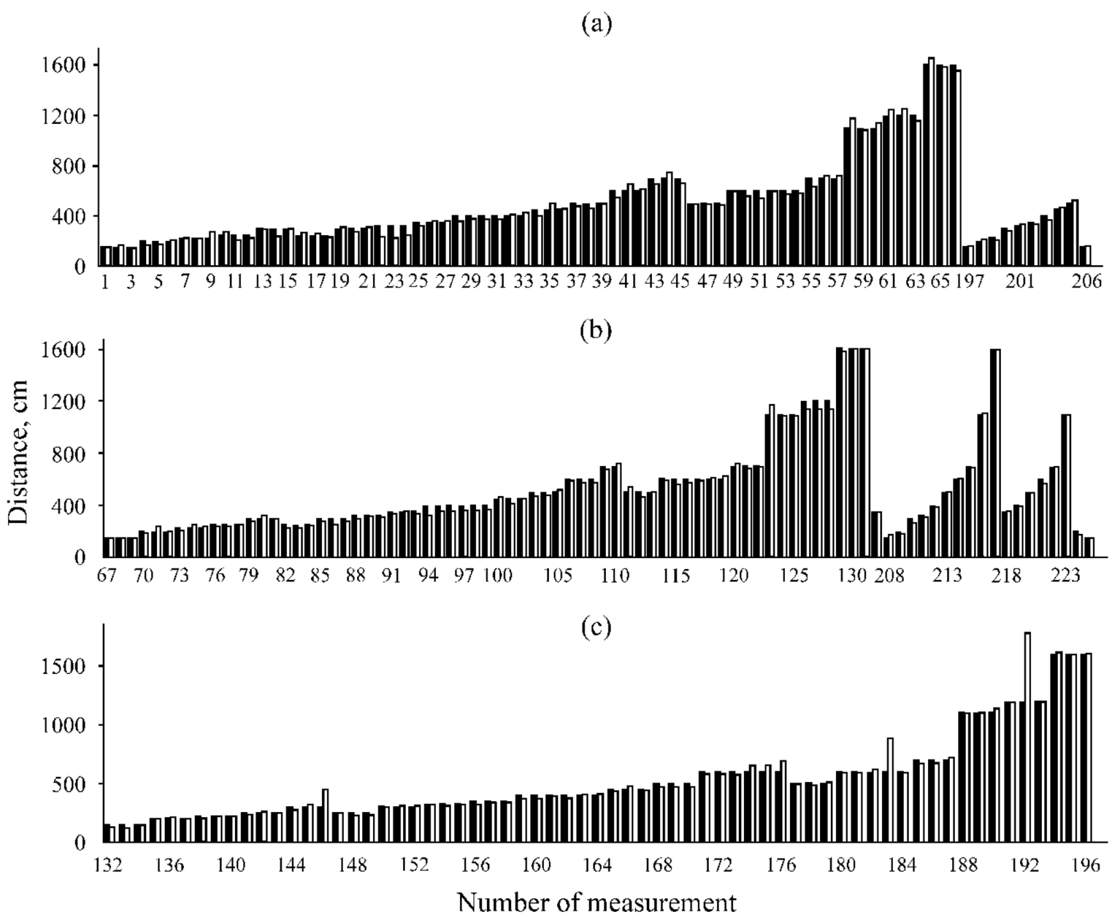

Fig. 3. Actual and calculated distances for (a) outdoor environment, (b) indoor environment, (c) underground environment: Black bars in the charts show the actual distance value between the transmitting device and the reference receiver during the experiment, and the white bars show the distance value calculated by equation (1).

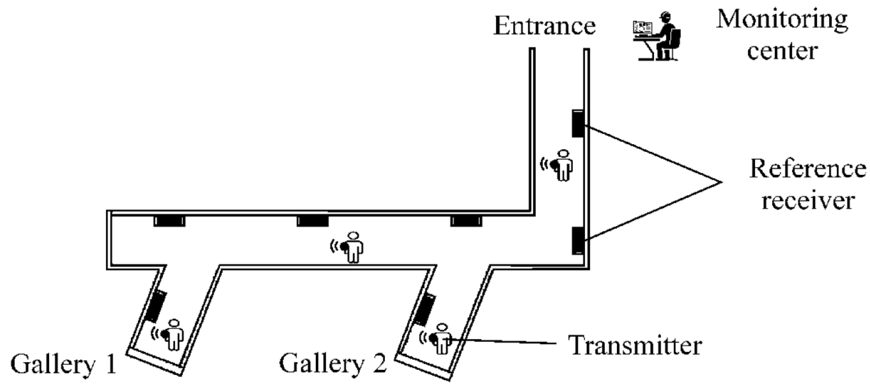

Fig. 4. The structure of the designed monitoring system.

3. PROPOSED SYSTEM

A miner monitoring system is designed for underground conditions (Fig. 4). Depending on the environment in which this system will be used, the number of gallery, transmitter, and reference receiver may vary. In the system, there are stationary reference receivers connected to a monitoring center. Each miner in the system has a transmitter that broadcasts an RSSI signal. Reference receivers send these RSSI signals broadcasted from transmitters to the monitoring center. By using these signals, the distance between the miner and the nearest reference receiver is determined. Since the locations of the reference receivers are stationary, the distance of the miner to any location can be calculated easily.

The dataset is created over this designed system. The calculated distance is affected adversely from environmental factors, and it becomes a necessity to change the environment coefficient k manually to reduce this affect. The environment, environment coefficient, actual and calculated distances are used as features of the model. Normalization of the features is done for feature scaling process. After that, training and test data are determined as 70% for training and 30% for testing. In the training data, "environment", "calculated distance" and "actual distance" are used as input values, and "environment coefficient k" is used as the desired output. Finally, the developed LSTM model is trained with these data. The structure of the LSTM model designed for this study is given in Fig. 5. In this model, an input layer consisting of 3 neurons, a hidden layer consisting of 32 LSTM layers and one neuron in output layer are used. The environment, the calculated distance, and the actual distance represent the three inputs. The dense layer is obtained by performing the node dropout process in which important weights are determined. This system gives the optimal environment coefficient k as the output. Based on the performance evaluation of the model, k is calculated with an accuracy rate of 97.14%.

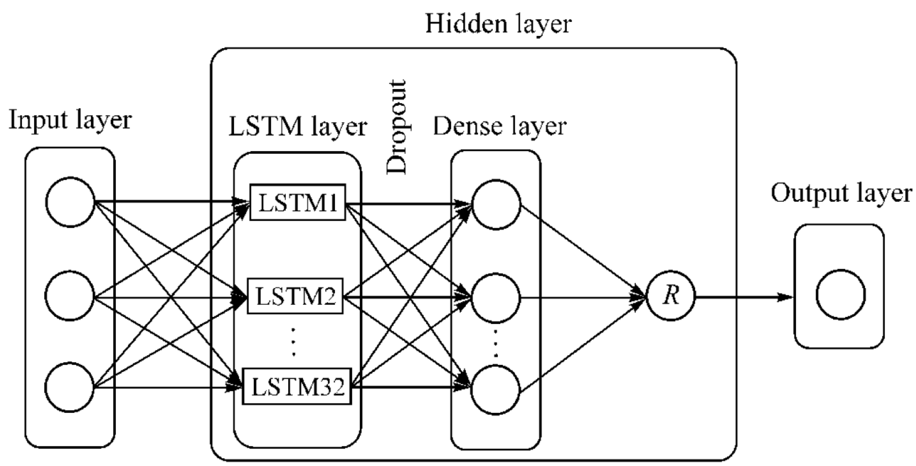

Fig. 5. LSTM network structure: R—activation of rectified linear unit.

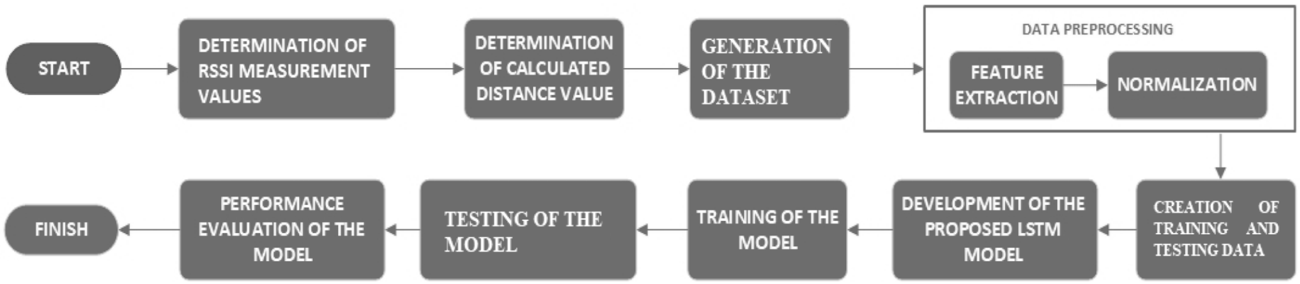

Fig. 6. Block diagram of the proposed system.

The block diagram of the proposed miner monitoring system is given in Fig. 6.

4. EXPERIMENTAL RESULTS

An LSTM model was developed using a dataset obtained through the IoT system created to monitor miners. Experiments of the model that give the k environment coefficient as an output, which ensures the calculation of the optimal distance of the miners to the nearest receiver, were carried out. Here, the goal is to have information about the location of the miner working in the underground mine and to ensure the ability to intervene in the correct location in a possible emergency event. Performance metrics are error measures which are necessary to evaluate the results of regression applications. In our study, we will be using the performance metrics “Accuracy”, “Root Mean Square Error (RMSE)”, “Mean Absolute Error (MAE)”, “R-Squared (R^2)”, and “Mean Absolute Percentage Error (MAPE)” in order to compare the obtained results:

RMSE shows the error distribution from a broad perspective. It is defined by the following formula:

$$\text{RMSE} = \sqrt{\frac{\sum_{j=1}^{n} e_j^2}{n}};$$

MAE is a very commonly used metric to measure the accuracy of prediction results. The formula for MAE can be given as follows:

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n} \left| e^t \right|;$$

MAPE indicates the accuracy as a percentage ratio defined by the formula:

$$\text{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n} \frac{e^t}{y^t};$$

R^2 is the proportion of the variation in the dependent variable that is predictable from the independent variables. It can be defined with the following equation:

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_t)^2}{\sum_i (y_i - \overline{y}_t)^2}.$$

In the above equations, e is the error calculated by the difference between the actual value and the predicted value, n is the number of observations; y, $\hat{y}$ are the actual and predicted values, respectively.

Experiments on the designed LSTM model were carried out based on different epochs. Table 3 presents the values of statistical parameters.

Table 3. Experimental results

Epoch	Accuracy, %	RMSE	MAE	R^2	MAPE, %
100	94.2857	0.569844	0.0955364	0.581279	0.922194
200	97.1429	0.590166	0.0219730	0.550882	0.620171
500	95.2381	0.657668	0.0113096	0.442268	1.000250
1000	95.2381	0.657668	0.0113096	0.442268	1.000250
5000	77.1429	5.315270	0.0732450	35.430400	12.448800

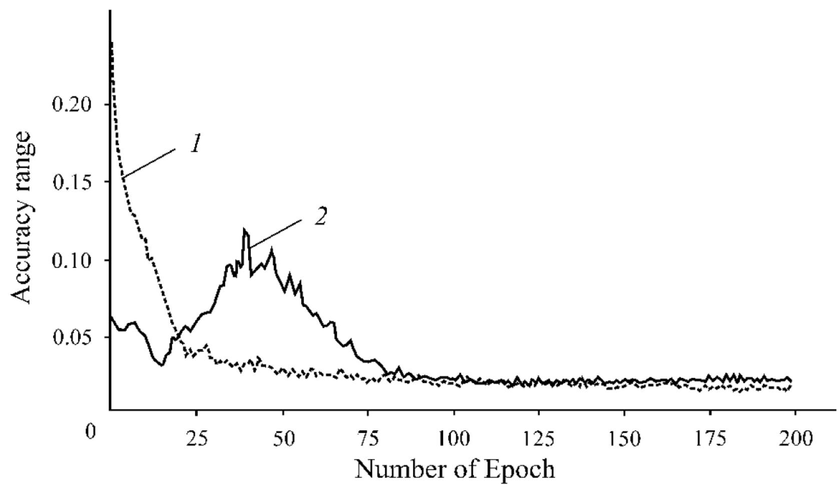

Fig. 7. Training loss of the model trained with 200 Epoch: *1*—training loss; *2*—validation loss.

Training of the LSTM model at different epoch values gave different accuracy rates. The most successful result was achieved with 200 epochs (Table 3). Therefore, the best result was obtained with an accuracy rate of 97.14% for estimation of environment coefficient *k*. This rate indicates that the designed miner monitoring system can be used effectively in practice. Figure 7 shows a graph related to the training loss and validation loss of the model trained with 200 Epoch. Loss values are used to show the success of the proposed model. Reduction of loss over time refers to the successful results in the implementation process of the model.

CONCLUSIONS

In this study, a miner monitoring system was developed for the aim of calculating the location of the miners in a possible accident that may be occurred in an underground mine. RSSI signals are broadcasted from transmitters that are on the miners in the designed system. These signals are read on stationary reference receivers and transmitted to the monitoring center. Using these RSSI signals collected in the center, the distances of the miners to the nearest reference receiver are calculated by location formula. It was observed that environmental factors, such as the size of the environment, objects in the environment, and obstacles encountered in the propagation of the signal, caused an error in this calculated distance value. To avoid these errors, the environment coefficient in location formula should be manually adjusted. Therefore, the LSTM deep learning architecture was implemented in order to automatically estimate this coefficient. A miner monitoring system was proposed using the IoT technology whose accuracy was improved with the designed LSTM model. Experiments were carried out to analyze the effectiveness of the results of the proposed system and the obtained accuracy outcomes showed that the designed miner monitoring system can be used effectively in practice.

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