Online Deep Transfer Learning and Multi-Sensor Analysis for Enhanced Underground Monitoring

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***Abstract*—Underground environments present unique challenges for monitoring hazardous conditions due to their complex and dynamic nature. Current prediction methods often suffer from data scarcity, especially during the early operation phases, and fail to adapt to changing conditions. This paper aims to address these issues by integrating multi-sensor analysis with online transfer learning techniques to enhance methane concentration monitoring in underground settings. The methodology involves training a baseline Long Short-Term Memory (LSTM) model on open-source data from a Polish coal mine and fine-tuning it using an online learning approach with data obtained from a Chinese coal mine. The results demonstrate significant improvements in prediction accuracy and reliability, especially during the initial stages of monitoring when data are sparse, achieving an R^2 value of 0.93 when using the online transfer learning model. This study helps improve the safety and efficiency of underground monitoring systems by addressing initial data scarcity and enhancing model adaptability to dynamic environmental conditions.**

Keywords—Multi-Sensor Analysis, Long Short-Term Memory (LSTM), Online Transfer Learning, Dynamic Underground Monitoring, Methane Concentration Prediction

I. INTRODUCTION

Operating in underground environments presents distinct challenges and dangers compared to their above-ground counterparts. These challenges include spatial complexity, geological unpredictability, inadequate ventilation, and the release of hazardous substances such as gases and dust [1, 2]. The variability of underground settings, characterized by fluctuating geological factors and gas emissions, poses dynamic risks jeopardizing worker safety and surrounding infrastructure [3, 4]. In the context of coal mining practices, methane, a byproduct of coal formation, presents a persistent hazard, with its accumulation considered extremely explosive when it reaches between 5% and 15% [5]. However, miners typically halt operations once methane concentrations go above 1%, preventing the levels from nearing the explosive range. This interruption causes significant productivity loss in mining operations, resulting in millions of dollars in financial loss [6]. Hence, continuous monitoring and prediction strategies are indispensable for ensuring the safety and sustainability of underground operations [7].

Underground spaces are usually equipped with advanced digital systems for monitoring and sensing purposes [8]. These systems also feature specialized tools to detect and manage natural hazards such as dangerous methane concentration levels. The Internet of Things (IoT) has further enhanced real-time data collection, monitoring, and early warning capabilities in these settings [9]. These technologies provide real-time information on environmental conditions like temperature, humidity, and hazardous gas levels [10]. Despite the vast amount of data generated, current monitoring systems primarily use it for visualization and rely on engineering professionals for analysis. However, visual analysis of multivariate sensor data streams is a complex task. Consequently, valuable data often remains underutilized, failing to provide meaningful insights into potential risks [11].

Advanced sensing technologies in underground environments encounter another significant challenge due to the incompatibility among various data sources [12]. Traditional statistical models find it difficult to handle the large volume of multi-sensor data, resulting in issues with accuracy and robustness, which hampers their ability to generalize across different projects [13]. Additionally, in the early phases of a new project, there is typically a scarcity of data available for informed decision-making, and the transfer of knowledge and experience from previous projects may be flawed [14]. Here again,

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professional expertise plays a pivotal role, yet this knowledge can be subjective and susceptible to errors.

This paper aims to enhance the accuracy and reliability of methane concentration monitoring and prediction in underground environments through the integration of multi-sensor analysis and online transfer learning techniques. A robust prediction model is developed by leveraging a baseline Long Short-Term Memory (LSTM) model trained on a dataset from a Polish coal mine, which is then fine-tuned in an online manner using a dataset from a Chinese coal mine. By combining data from various environmental sensors and applying advanced deep learning models, the paper captures the complex temporal patterns and dependencies in methane concentration time series. Additionally, the paper explores the practical applications of online transfer learning to continuously adapt and improve model generalization across different underground scenarios, ultimately contributing to safer and more efficient underground monitoring and prediction systems.

II. Background Review

This section provides a concise overview of relevant studies that inform the integration of multi-sensor analysis and deep transfer learning for enhanced underground monitoring.

A. *Multi-Sensor Predictions in Underground Environments*

Reference [15] developed a combined prediction model based on the dynamic optimization of indicators and Bi-directional LSTM networks (Bi-LSTMs) to predict gas concentration in coal mines. The methodology involved using Spearman's rank correlation coefficient to dynamically optimize prediction indicators and then applying Bi-LSTMs to extract time series and spatial topology features from these indicators. The model predicted gas concentration for the next 30 minutes with high accuracy, showing an average R^2 of 0.965 and a prediction efficiency of 79.9% for abnormal or normal gas emissions. The outcomes suggested that this method significantly improved the accuracy of gas concentration predictions compared to traditional methods, which enhanced early warning systems and safety measures in coal mines. Despite the widespread application of prediction models, especially data-driven models, in improving prediction accuracy, further research was needed to address the cold start problem when deploying prediction and monitoring systems at new underground sites [16]. Traditional models require a substantial amount of pre-existing data to train effectively, which is not always available at the beginning of new projects. This data scarcity poses a challenge in real-time applications, highlighting the necessity for models that can adapt and learn incrementally as new data becomes available.

B. *Transfer Learning Applications in Monitoring*

Transfer learning is a subset of machine learning techniques where a model developed for a specific task or domain is reused as the starting point for a model on a different but related task or domain. Transfer learning is a widely adopted approach for cases in which the acquisition of data is challenging and the available data sets are minimal. The applications of this approach extend to monitoring environmental indicators across multiple domains. For example, reference [17] automated the identification of native and invasive plant species using drones and deep transfer learning. The authors collected a dataset with 10,000 images, processed and augmented them, and applied several pre-trained deep convolutional neural network models for feature extraction and classification. The model, combined with data augmentation and hyperparameter optimization, achieved the highest accuracy of 94%.

Underground operations are a domain where data scarcity is a significant and persistent issue. Reference [18] focused on the retrieval of soil heavy metal content in a mining area for environmental monitoring using transfer learning techniques. Initially, a model was pre-trained with soil samples from the source domain in 2017 and then retrained with a smaller set of samples from the target domain in 2019. This model was utilized to estimate the content of Cu and Pb at various sites in the study area in 2019, with the spatial distribution of these elements mapped accordingly. While the results demonstrated the effectiveness of the model in estimating heavy metal content, the study acknowledged the need for more soil samples to further enhance the model's performance. Reference [19] presented a framework for real-time heat release rate inversion of tunnel fires using deep learning and transfer learning. The researchers utilized large-scale databases and transfer learning methods to predict tunnel fire states accurately, even in complex scenarios with double fire sources and limited temperature sensor data. By training deep learning models on rich source domain datasets and fine-tuning them on target domain datasets, the study successfully extended the applicability of the models to different full-scale tunnels while reducing computational resource requirements.

Despite these advancements, the reliance on large initial datasets before implementation remains a critical limitation. This paper addresses this gap by incorporating online learning techniques with transfer learning, allowing the model to update continuously as new data is collected. This approach not only mitigates the data scarcity issue at the beginning of underground projects but also ensures that the model remains adaptable to changing environmental conditions, ultimately improving the accuracy and reliability of monitoring systems in underground environments.

III. Experiments and Results

This section presents the experimental setup, methodologies, and results of the study on integrating online learning and transfer learning for enhanced underground multi-sensor monitoring.

A. *Description of Data Sources*

The first dataset used to train the baseline LSTM model comes from an open-source dataset collected from a longwall underground coal mine in Poland. It covers the period from March 2, 2014, to June 16, 2014, capturing data from 28 strategically positioned sensors throughout the mine. This dataset consists of 9,199,930 samples recorded at one-second intervals and is notable for its completeness and reliability, with no missing values. This dataset was initially introduced in [20]. In this paper, data from five methane concentration sensors, a wind speed sensor, and a temperature sensor, all located in the working face, were used to train the baseline LSTM model.

A second dataset was utilized for training the online forecasting model. This dataset was obtained from a longwall underground coal mine in China. The dataset included measurements from five methane concentration sensors, a temperature sensor, and a wind speed sensor positioned at the mine's working face. Data collection spanned from January 3, 2022, to May 12, 2023, encompassing a total of 494 days. Data were recorded at one-minute intervals, yielding average values for each sensor, resulting in a dataset comprising 710,367 data samples.

B. *Data Preprocessing*

The Polish dataset was already clean and free of missing values. In contrast, the Chinese dataset contained missing values marked as *NaN*. During data preprocessing, these missing values were identified and imputed with the most recent valid values. The methane concentration sensors in the Chinese mine were subjected to regular testing with abnormal accumulation levels. These anomalies were identified and replaced with previous valid data points. Given the sensitivity of methane concentrations near the working face, the closest methane concentration sensor to the working face in both datasets was selected as the target variable. To ensure consistency between the two datasets, the order of the sensors in each dataset was synchronized based on the similarity of the type and location of the sensors. Additionally, the Polish dataset, which had an original data interval of one second, was resampled to one-minute intervals by averaging the data points within each minute. Finally, sliding time windows of 6 minutes were constructed for both datasets.

C. *Baseline Model Training*

Following the preprocessing stage, 153,393 minutes of data from the Polish database were used to train an LSTM prediction model. 80% of the initial data was used for the training process, the next 10% for validating the prediction results, and the final 10% for testing the model. This model consisted of two LSTM layers and two dense layers. Each of these hidden layers contained a set of neurons, transforming the information from the previous layer to the next layer [21]. The architecture of the prediction model is shown in Fig. 1. The ReLU activation function was used for its simplicity and effectiveness in making the model non-linear. Additionally, the Adam optimizer with a learning rate of 0.001 and the mean squared error loss function were used to optimize the model's learning. The batch size was set to 256. Hyperparameters such as the number of neurons, learning rate, and batch size were tuned using random search, which involved sampling from specified ranges and evaluating model performance to identify the best combination.

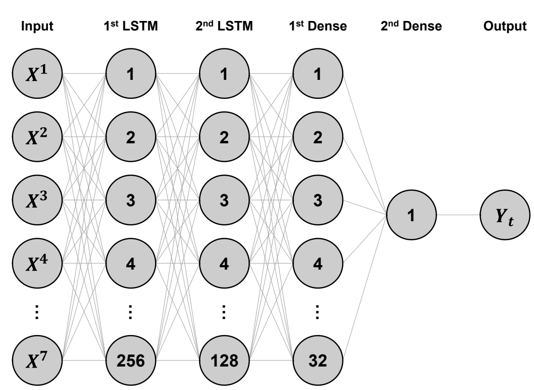

Fig. 1. Architecture of the baseline LSTM model.

The training process was conducted using the Keras package in Python [22]. The Polish data was fed into the model in batches, and the model's parameters were updated after each batch to minimize the loss function. The model was trained for a total of 50 epochs.

To evaluate the performance of the model, three metrics—Mean Absolute Error (MAE), Mean Squared Error (MSE), and Coefficient of Determination (R^2)—were used. MAE calculates the average of the absolute differences between the actual and predicted values. MSE computes the average of the squared differences between the actual and predicted values. R^2 measures the proportion of the variance in the dependent variable that is predictable from the independent variables. An R^2 score close to 1 indicates a high level of prediction accuracy, while for the first two metrics, values closer to 0 are more favorable.

Fig. 2 shows the evolution of the training and validation loss over the 50 epochs, indicating how well the model learned over time. The model's performance on the validation set was continuously monitored. The model with the lowest validation loss was saved as the baseline model. The performance of this baseline model was then evaluated using the test dataset. Fig. 3 presents a comparison between the actual and predicted methane concentrations on the test dataset. This plot illustrates the model's ability to predict methane concentration accurately on the unseen test data. Additionally, the MAE, MSE, and R^2 values were 0.02, 0.03, and 0.97, respectively.

D. *Online Transfer Learning*

Online learning is a method of machine learning where the model incrementally updates its parameters as new data appears [23]. This method is different from traditional batch learning methods, which use the entire dataset at once to train the model. Online learning is particularly useful for scenarios where data is continuously produced. This continuous data helps the model dynamically adapt to changing conditions. Therefore, online learning is a suitable tool for monitoring and predicting

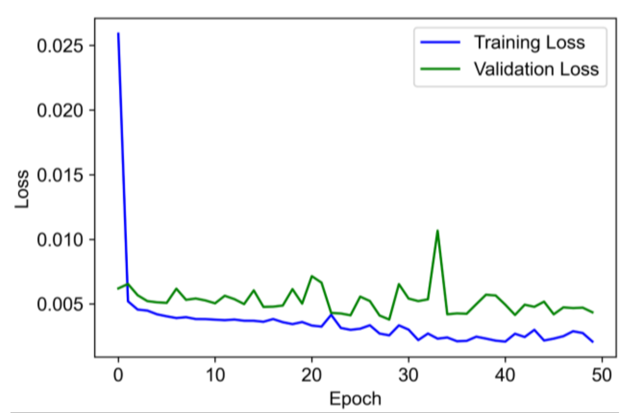

Fig. 2. Evolution of the training and validation loss of the baseline LSTM model over epochs.

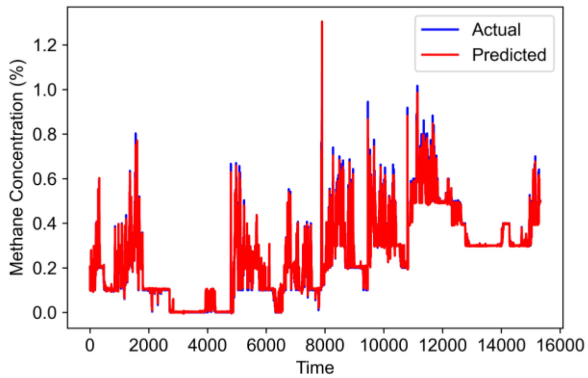

Fig. 3. Comparison of actual and predicted values by baseline LSTM model on testing set.

conditions in underground environments where the situation changes rapidly.

In this section, two scenarios were explored to predict methane concentrations in a Chinese coal mine using online learning with LSTM models. In the first scenario, an LSTM model with the same architecture and hyperparameters depicted in Fig. 1 was trained exclusively on the Chinese dataset without any pre-trained baseline model. Sliding time windows were sequentially fed into the LSTM model to simulate real-time data generation and online learning conditions. In this way, as new data arrived, the model updated its parameters incrementally, learning continuously from the incoming data. The *train_on_batch* function of the Keras package in Python was utilized for this purpose.

The performance of the LSTM model was evaluated at each time step using MAE, MSE, and R^2 metrics. Fig. 4 illustrates the actual methane concentrations compared to those predicted by the online model. Initially, the model's performance was relatively poor due to the lack of sufficient training data. However, as more data were processed, the performance improved steadily. By the end of the learning process, the MAE and MSE reached 0.01 and 0.0005, respectively, and R^2 showed an acceptable value of 0.93.

In the second scenario, the online learning model benefited from transfer learning by leveraging the baseline model pre-

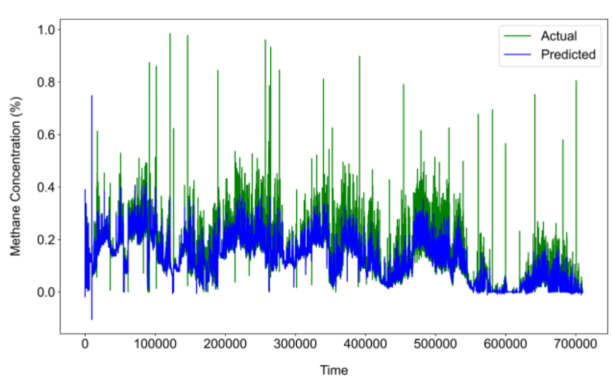

Fig. 4. Comparison of actual and predicted results by the online LSTM model, without the baseline model.

trained on the Polish dataset. This pre-trained model served as a starting point, providing an initial set of parameters aimed at improving the model's performance during the early stages of the online learning process. The same sliding time windows were used to update the model with the Chinese dataset, allowing it to adapt to the new data while retaining the knowledge from the Polish dataset.

The final results of the online model evaluation in this scenario were approximately similar to the results obtained in the first scenario, with slightly better metrics for the second scenario. This was expected due to the significantly larger amount of data in the Chinese dataset compared to the Polish dataset. However, a notable difference between the prediction results in the two scenarios was that the model with the baseline achieved higher performance much faster than the model trained from scratch in the first scenario. The R^2 score for the first scenario after training the model with the initial 3000 data points was 0.88, while this metric for the second scenario after the same period was 0.94. The increase in the initial R^2 score compared to the first scenario was due to the transferred knowledge from the Polish dataset, leading to more reliable predictions during the initial phase of online monitoring.

E. Discussion and Implications

The online transfer learning model, which was initially trained with data from a Polish mine and subsequently refined using simulated real-time data from a Chinese mine, achieved an R^2 score of approximately 0.93. This high accuracy underscores the model's effectiveness in capturing intricate temporal patterns, which is essential for reliable methane concentration predictions. Compared to traditional methods, which often rely heavily on extensive pre-existing datasets and encounter challenges with adaptability, this approach offers significant advancements. The model's ability to rapidly adapt to new data enhances safety by enabling timely interventions and reducing accident risks. Additionally, it improves operational efficiency by minimizing unnecessary shutdowns caused by false alarms, thereby saving costs and boosting productivity. Integrating historical data from another mine to refine predictions in an active mine demonstrates the model's innovative use of past experiences to overcome data scarcity and improve monitoring systems. This approach represents a practical enhancement over existing methods by addressing limitations related to data availability and adaptability.

IV. Conclusion

A baseline LSTM model was trained with open-source data from a Polish coal mine. This model was then incrementally fine-tuned using an online learning method with data from a Chinese coal mine. This two-step process was designed to leverage transfer learning to improve the model's initial performance and adaptability. The baseline model, trained on the Polish dataset, provided a strong foundation, while the online learning component allowed the model to continuously update as new data became available from the Chinese mine.

The results indicated faster improvements in the prediction accuracy and reliability of methane concentration levels. Specifically, the model achieved an initial R^2 value of 0.94 when using the pre-trained baseline model for the first 3000 data points, while the initial R^2 value for the online learning model without the baseline model was 0.88 for the same period. This improved performance underscores the effectiveness of the online transfer learning model in addressing the initial data scarcity problem and maintaining high accuracy as more data are collected.

This research enhances underground monitoring by demonstrating the practical application of online transfer learning combined with multi-sensor data analysis. The developed model not only improves the safety and efficiency of monitoring systems but also offers a scalable solution that can be adapted to various underground settings. By continuously updating the model with new data, this approach ensures that the monitoring systems remain responsive to dynamic environmental conditions, ultimately enhancing overall risk assessment and mitigation strategies in underground operations. Future work will involve validating the approach across diverse underground sites, incorporating additional hazardous gases, and analyzing the model's long-term adaptability and performance.

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