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REVIEW ARTICLE

Review on Machine Learning-Based Underground Coal Mines Gas Hazard Identification and Estimation Techniques

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Abstract
The underground coal mines (UCM) exhibit many life-threatening hazards for mining workers. In contrast, gas hazards are among the most critical challenges to handle. This study presents a comparative study of the sensor fusion methodologies related to UCM gas hazard prediction and classification. The study provides a brief theoretical background of the existing methodologies and their usage to mitigate the gas hazard issues in UCM. A brief comparison report emphasising the advantages and disadvantages of the existing models related to the UCM gas hazard monitoring is presented. Additionally, a separate comparison is also drawn, considering only neural network models based on their prediction accuracy and other performance metrics. This study attempts to observe and compare the Neural network models with the conventional method in the field of UCM gas hazard prediction, which is not explored in this fraternity.

1 Introduction

The underground coal mines (UCM) environment is entirely different from other industries. It imposes many life-threatening hazards on the mining workers. A reliable, real-time hazard monitoring system is required to ensure occupational safety. Based on the mining process, coal mines are classified into two categories, i.e., open cast and underground mines [95]. Underground mines are considered the most challenging and hazardous work environment. A brief classification of the UCM hazards as per literature [71] is mentioned as follows.

1. Rock burst hazard—A sudden violent destruction of rock mass due to the instantaneous release of elastic deformation energy [72]. These kinds of hazards are often followed by coal or rock mass ejection and airwaves that may be destructive.
2. Mine fire—These hazards are mainly associated with the continuous coal combustion phenomena. It mainly occurred due to the oxidation of residual coal in the goaf area [53]. These hazards are often followed by fire-damp explosions and coal dust explosions, resulting in disasters responsible for fatal accidents.
3. Dust hazards—Mining of the coal body is responsible for dust formation, and this dust transmits across all the mining galleries through the mine ventilation system, thus resulting in mine atmosphere contamination [12].
4. Coal and gas explosion hazards—Parameters responsible for explosion hazards in UCM are fuel, oxygen, ignition source and confinement. The fuel can be the optimum level of combustible gases and coal dust. For the UCM case, 5 to 15% methane concentration in the air is considered a flammable mixture [74]. The ignition source can be a spark from electrical or mechanical equipment or operations, continuous combustions, and many others.
5. Water hazard—These hazards arise due to hydrogeological conditions. The mining process in difficult conditions of aquifers may lead to increased water hazards [53]. Floods are common examples of these types of hazards.

Various other hazards in the UCM originate due to the challenging UCM environment, but the above-mentioned hazard classes are among the most common. Based on fatality frequency of occurrence, gas-related hazards are considered

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the most significant, as historical evidence shows relatively larger fatalities in this hazard class. Table 1 shows the evidence of fatalities reported by various literature in UCM cases. From Table 1, it is prevalent that gas-related hazards are associated with the greater proportion of fatalities in history. Hence, there is a requirement of identifying the state-of-the-art models in gas hazard monitoring for the UCM scenario.

Several studies have presented a detailed review of underground coal mines' gas hazard monitoring and identification technologies. Szlązak et al., in the literature [89], presented an assessment of current methods of methane control during multi-seam extraction by longwall mining in Polish mines. The study in literature [52] has discussed the various UCM gas hazard indicator gases and their monitoring methods. Literature [33] has reviewed the early warning monitoring technology related to rock burst hazards in coal mines. The literature [74] has emphasized the factors affecting the explosion hazards in the UCM and their associated preventive measures.

Similarly, the authors in the literature [65] have reviewed the recent trends in UCM gas hazard monitoring dedicated towards the application of wireless sensor networks. All these methods are emphasized in the UCM hazard monitoring and mitigation. However, none of the literature has effectively reviewed the effectiveness of machine learning (ML) methods in UCM gas hazard identification. Table 2 briefs the objectives of several existing studies that reviewed the UCM hazard and safety for the last two decades.

Table 2 prevails that most of the existing literature reviews are only dedicated towards mining operations, wireless sensor networks, and the assessment of disasters. With the advancement of computational power and artificial intelligence (AI) technologies, the application of ML is being investigated in UCM scenarios. However, to the best of the authors' knowledge, no comparative review related to the application of ML against the UCM gas hazard prediction is presented.. Therefore, this study aims to explore the advancements in ML-based UCM hazard identification and monitoring techniques and compare the conventional and ML-based hazard identification methods. The contribution of the study is as follows.

1. The application of popular prediction and estimation methods in UCM gas hazard identification is discussed.
2. The comparison of conventional methods with the artificial neural networks in the context of UCM is presented.
3. The limitations of existing ML-based gas hazard identification and prediction models are explained.

Table 1 Comparison of fatalities in commonly occurring hazards

Country/period	Gas explosion and poisoning (%)	Fire (%)	Rock brust + roof collapse (%)	Water/flood	Other (%)
China, 2001–2015 [60]	64.72	4.08	8.46	16.84	5.9
India, 2001–2014 [91]	3.36	–	55.14	–	41.5
Poland, 2008–2017 [14]	82.2	0.0	15.6	2.2	0.0
USA, 1900–2006 [41]	89.52	6.26	0.71	–	3.51

Table 2 Review studies related to UCM hazards and safety

Authors/Literature	Repository	Year	Review objective
Wang et al. [98]	Springer	2022	Ground warer Inrush Hazard
Verma and Chaudhari [97]	ScienceDirect	2016	UCM hazard risk assessment techniques
Muduli et al. [65]	ScienceDirect	2018	Application of wireless sensor network for environmental monitoring in UCM
Black [10]	ScienceDirect	2019	Coal and gas outburst in Australian coal mines
Szlazak et al. [89]	Springer	2020	Control of methane emission during multi-seam extraction of longwall mining in Polish coal mines
Ray et al. [74]	ScienceDirect	2022	Study the disasters occoured in the coal mines in last two daceds
Kumar [43]	Springer	2015	Rescent innovation in mining equipments related to safety
Shahmoradi et al. [83]	MDPI	2020	Application of drones in UCM
Mardonova and Choi [56]	MDPI	2018	Wearable device technology for mining industries
Reddy et al. [75]	IEEE	2016	WSN and monitoring technologies for mine safety
Dohare et al. [24]	Taylor & Francis	2015	Wireless communication and environment monitoring in underground coal mines
Jung and Choi [38]	MDPI	2021	Application of ML in mining exploration, exploitation and reclamation

4. This study can help identify the suitable ML methodology for UCM gas hazard monitoring scenarios.

2 Background

2.1 Gas Hazards Constraints in UCM

UCM gas hazards constitute a larger proportion of accidents and fatalities. The gas responsible for hazards in the UCM can be classified into two groups, i.e., toxic and flammable gases. Various toxic and flammable gases present in the UCM are already discussed in the literature [26, 41, 44, 69, 70]. The toxic gases directly impact the worker's health and well-being if they exceed their threshold limit values (TLV). Moreover, the flammable gases do not affect miners' health directly, but due to their flammability properties, they may result in gas or coal-dust explosion, which is fatal and life-threatening too. A brief explanation of these gases is presented in Table 3.

Apart from these gases, temperature and humidity are also significant parameters determining the effectiveness of the mining workers. Furthermore, these parameters also affect the flammability limits of gases like CH_4. Hence, these parameters must be considered to design an effective gas hazard monitoring and prediction system.

2.2 Underground Mine Gas Monitoring System

The UCM gas monitoring has been extensively investigated for a safe and reliable operation throughout mining history. A study in literature [82] has discussed the methane airflow pattern in a longwall mining operation. The gas pattern was monitored using the automatic methane monitors fixed throughout the length of the longwall face. Another study in Schatzel et al. [81] presented the consequences of methane emission due to the increased longwall face length. This study also adopted a similar approach to monitor the methane across the longwall face. Moreover, these studies adopted statistical tools like linear regression to realise the gas pattern. The main concern in this approach is that only a single attribute is used for such analysis.

However, the gas concentration may depend on other parameters like ambient environment and ventilation status. Various gases in the underground coal mines pose a non-linear and complex relationship that is hard to realise using a physical model; therefore, several studies adopted the artificial intelligence (AI) approach. The AI-based deep neural network (DNN) models can extract the non-linear and complex rules among various attributes to reach a dedicated solution. The study [93] proposed the artificial neural network (ANN)-based methane forecast model. The study proposed multiple multilayer perceptions (MLPs) for various

Table 3 Hazardous gases in UCM

Gas	Property	Impact	Source
Methane (CH_4)	Colourless, odourless,tasteless, flammable, lighter than air	Asphyxiation, dizziness, headache, and nausea in high concentrations due to the displacement of oxygen, explosion (5%–15%)	Trapped in coal seams released during the mining process
Carbon monoxide (CO)	Flammable, colourless, tasteless, odourless, lighter than air, and toxic	At 200 ppm, slight headache, tiredness, dizziness, nausea after 2 to 3 h; at > 200 ppm, life-threatening after 3 h	Coal Mine spray painting, spontaneous coal combustion in goaf, gas explosion, coal dust explosion
Carbon dioxide (CO_2)	Colourless, odourless, heavier than air, suffocating	At 5%, stimulated respiration; at 7% to 10%, unconsciousness after few minutes of exposure	Workers' respiration, coal seam or rock oxidation process, underground blasting
Hydrogen sulphide (H_2S)	colourless, slightly sweet, rotten egg flavour, flammable, toxic, heavier than air	The concentration of 0.005–0.01% will cause irritation in the eyes and respiratory tract after 1.2 h, the concentration more than 0.01% will result in death in a short time. Explosion (> 45.5%)	It is generated during combustion of gunpowder, explosion of substances including sulphide, and drainage of water in flooded areas
Nitrogen dioxide (NO_2)	Reddish-brown colour in high concentrations, acrid or bleach odour, non-flammable, heavier than air	At 1–13 ppm, irritation of nose and throat; ≤ 80 ppm, tightness in chest after 3 to 5 min; > 80 ppm, pulmonary enema after 30 min	Produced by underground blasting in coal mine
Hydrogen (H_2)	Colourless, reacts easily with other chemical substances, explosive mixtures are easily formed, lighter than air	High concentration causes oxygen-deficient environment, headaches, ringing in ears, drowsiness, nausea, skin having blue colour	As a result of coal gasification [9]

locations in the underground coal mines and achieved significant forecasted results for all the MLPs. Apart from the methane-related studies, several studies, like Bonetti et al. [11], presented the monitoring of other gases, including methane. Gas monitoring and estimation is one aspect of the gas monitoring system, and another is communication among the sensor nodes—reliable communication between the sensor nodes for adequately implementing the gas hazard monitoring system. The wired communication system is the conventional approach in UCM. However, the dynamic and complex working environment imposes various critical challenges, like mechanical damage to the wired communication setup. Therefore, several studies like Chen and Wang [17] and Muduli et al. [65] are intended for the development of a wireless sensor network (WSN) that leverages the advantages of wireless networks. However, the underground mine geometry and coal properties restrict the full-fledged WSN implementation. Therefore, the literature survey in this study covers both aspects, i.e., challenges associated with the current gas hazard monitoring prediction and estimation and limitations imposed by the wired and wireless sensor network.

3 Review Process

Following steps are adopted to review the existing prior arts related to ML-based hazard identification in UCM scenarios.

1. Defining the research questions: The following research questions are formulated to start the review process.

    (a) What are the available hazards in UCM cases?
    (b) What are the existing hazard identification and monitoring methods?
    (c) What is the application of ML technologies in UCM, and how are they affecting the environmental safety of UCM?

    Based on the formulated research questions, the following search terms are identified.

    (a) Underground coal mines gas hazard.
    (b) Gas hazard Prediction.
    (c) Underground coal mines hazard monitoring.
    (d) Gas hazard Identification.
    (e) Gas hazard Forecasting in underground coal mines.
    (f) multi-sensor-data-fusion.

2. Selection of data source: For the study presented in this review, authors have considered the literature available in reputed journals and international conference proceedings. The considered electronic database are as follows.

    (a) IEEE Explore
    (b) ScienceDirect
    (c) SpringerLink
    (d) MDPI
    (e) Arxiv
    (f) Google Scholar

3. Identification of relevant literature: To identify the relevant literature for the review process, two factors are considered, i.e., date of publication and objective of the research work. The date of publication is considered between 2000 to 2022. Any literature considering at least one research term mentioned in Step 1 is also accepted for review.

The following sections discusses the existing literature on UCM gas hazard identification and prediction based on ML methods. The discussed articles are the outcome of the above-mentioned review process.

4 Gas Hazard Prediction and Estimation in UCM

This section discusses various existing studies related to UCM gas hazard monitoring, prediction, and estimation. The associated theories of each methodology are briefly explained, along with their application in the UCM gas monitoring system. Moreover, a brief comparison is also presented to identify the suitable option for the problem underhand.

4.1 Kalman Filtering

It is a recursive process for estimating the state of any physical phenomenon. A well-defined mathematical model of any physical process is required for the state estimation. It involves two steps, i.e., the prediction step and the update step. In the prediction step, an estimated value of a priori state is calculated as follows,

$$\hat{x}_k^- = F_{k-1}\hat{x}_{k-1}^+ + G_{k-1}u_{k-1} + L_{k-1}w_{k-1} \tag{1}$$

In (1), $\hat{x}_k^-$ is the a priori state for the kth time stamp, $\hat{x}_{k-1}^+$ is the a posteriori state of $(k-1)$th time stamp, u_{k-1} is the control input to the physical model, w_{k-1} is the process model noise for $(k-1)$th time stamp. F_{k-1}, G_{k-1}, and L_{k-1} are the state transition matrix, control input matrix, and process model noise sensitivity matrix. In this step, the process model covariance of $(k-1)$th time stamp is also propagated to the kth time stamp, given in (2).

$$\hat{P}_k^- = F_{k-1}\hat{P}_{k-1}^+ F_{k-1}{}^T + Q_{k-1}, \tag{2}$$

where $\hat{P}_k^-, \hat{P}_{k-1}^+$ are the priori and posteriori covariance of kth and $(k-1)$th time stamp and Q_{k-1} is the covariance matrix for the process model noise. The second step, i.e., the update step, uses the linear measurement model for the correction of the state. For the linear Kalman filter, the measurement model can be given as,

$$y_k = H_k x_k{}^- + M_k V_k, \tag{3}$$

where H_k is the measurement matrix, M_k measurement model noise sensitivity matrix, and V_k is the measurement model noise. The covariance matrix for the measurement model is given in (4).

$$S_k = H_k P_k{}^- H_k{}^T + R_k, \tag{4}$$

where R_k is the covariance matrix of measurement model noise. The state is updated as follows,

$$\hat{x}_k^+ = \hat{x}_k^- + K_k\left(y_k - H_k x_k{}^-\right), \tag{5}$$

where K_k is the Kalman gain that can be calculated as,

$$K_k = P_k{}^- H_k{}^T S_k \tag{6}$$

Again, the covariance of the update step also needs to be propagated to the next time step, which is mentioned in (7).

$$\hat{P}_k^+ = (I - K_k H_K)\hat{P}_k{}^- \tag{7}$$

Equations (1)–(7) represents the complete process of linear Kalman filtering. The other variants are Extended Kalman filter, Unscented Kalman filters and Ensemble Kalman filters. Further details in this regard are given in the literature [5, 16], but a minimal number of literature is dedicated to its usage for gas hazard prediction in the UCM. Literature [99] has adopted the Ensemble Kalman filter to estimate the methane gas dispersion in the main return airway. The model was developed considering the stationary and regular structure of the return airway. But the UCM environment is dynamic and very complex, making it challenging to be interpreted mathematically. Hence it becomes a challenging task to design the process model in (1) and the measurement model in (3). Another problem with this technique is its scalability. That is, as the mine geometry changes, there is a requirement to re-design the process model and measurement model.

4.2 Least Square

The least-square is a non-probabilistic method of parameter estimation. This method can estimate a parameter by minimising the objective function mentioned in (8).

$$J = \varepsilon_1{}^2 + \varepsilon_1{}^2 + \ldots + \varepsilon_k{}^2 = \varepsilon^T \cdot \varepsilon, \tag{8}$$

where ε is the measurement residual, it can be given as,

$$\varepsilon = y - H \cdot \hat{x} \tag{9}$$

In (9), y is the actual output of any process, $\hat{x}$ is the estimated state, and H is the measurement matrix. The optimal estimated state can be found by minimising the overall measurement residual in (8), which is given in (10).

$$\hat{x}_{opt} = (H^T H)^{-1} H^T y \tag{10}$$

The other variants of least squares are the weighted least square and the recursive least square. It is a method that estimates the parameters by minimising the squared distance between the data points and the regression line. For the UCM case, literature [81] used this method to estimate the parameter of a linear regression model to predict methane concentration. The disadvantage of this method is the requirement of a regression model before the procedure. On many occasions, it may require testing with multiple regression models to get an optimal model, making it time-consuming and resulting in suboptimal solutions for the estimates.

4.3 Maximum Likelihood

It is another parameter estimation technique; unlike least squares, this model accounts for the probability distribution function (PDF) of the observed samples. The likelihood function can be given as,

$$L(W|Y) = f\left(y_1|W\right)f\left(y_2|W\right)f\left(y_3|W\right)\ldots.f\left(y_k|W\right) \tag{11}$$

In (11), f represents the PDF, W is the parameter vector, Y is the sample vector, and $y_1 - y_k$ are the elements of the sample vector Y. To obtain the maximum likelihood estimate (MLE) of W parameters, the first order partial derivative of likelihood function L with respect to all the parameters in the W vector is computed as,

$$\frac{\partial L(W|Y)}{\partial w_i} = 0 \tag{12}$$

W_i is the i_{th} element of the W. Using (12), the estimated parameters associated with W can be obtained. For computational ease, instead of using (12), the partial derivative of the log-likelihood is preferred. More details about MLE can be observed in the literature [66]. In the UCM case, literature [4] used MLE for the parameter estimation of the negative binomial model for an injury variable indicator model. Apart from this work, no significant study is present in the field of UCM gas hazard prediction using the MLE. Again, this method accounts for a known PDF model with its parameter to be estimated. However, in the UCM case, the limited available data and its variability across different mines make it challenging to design a generic hazard prediction model using MLE.

4.4 Knowledge-Based Expert System

The Knowledge-based expert system (KBES) consists of the input as the sensor data, and it can be an image, environmental parameters like temperature, humidity, or anything that can be observed by means of a sensor. A typical schematic of a KBES is shown in Fig. 1. The KBES generate decisions based on the correlation between the input and the Knowledge base. The knowledge base consists of syntactic rules and parametric templates for decision-making. The rules can be in the form of an "IF-Then" statement. More details about this method are given in the literature [59]. Comparatively, this model is among the simplest techniques that can be directly deployed on small sensing devices like microcontrollers. Due to this fact, most of the gas detectors for UCM are based on this method. Literature [76] has proposed an IoT-based mine safety system using an Arduino controller, interfacing gas sensors, and a speaker as an alarm indicator. The alarm signals are designed such that a gas level rises to its maximum allowable limit, the speaker starts to ring. Literature [87] proposed an IoT-enabled smart helmet for UCM environment monitoring. The helmet consists of sensors as the input microcontroller that samples the sensor data and transmit it to a cloud server. In the cloud server, the sensed data are correlated with a predefined set of rules to generate the alarm signal. Literature [80] proposed a mine hazard alert system to mitigate fire, water, and strata-related hazards. Sensors integrated with microcontrollers for these modalities are used to serve the purpose, and a dedicated rule base is used for hazard identification. Similar kinds of studies can be observed in the literature [25, 36, 68, 85, 108] with a dedicated knowledge for hazard identification.

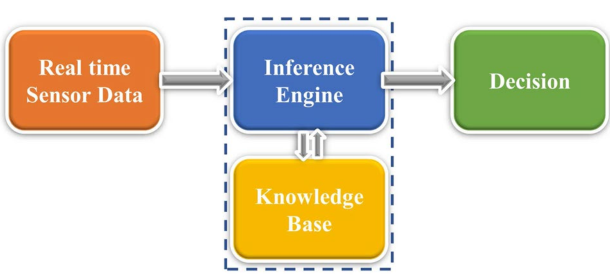


Fig. 1 Knowledge-based expert system

4.5 Fuzzy Set Theory

Fuzzy set-based inference models are suitable when there is vagueness in the input data, or the input data is fuzzified [39]. For vague data mostly represented by a linguistic variable, it consists of two steps. The first step is to develop a fuzzy rule base for the inference model, as mentioned in (13).

$$\begin{aligned} &R : IF(A_1 \ is \ S_{i1} \ AND \ A_2 \ is \ S_{i2} \ AND \\ &\quad A_3 \ is \ S_{i3} \ \dots . \ AND \ A_k \ is \ S_{ik}) \\ &THEN \ (O \ is \ D) \end{aligned} \tag{13}$$

The fuzzy rule mentioned above has an 'IF-THEN' structure containing some statements. The statement associated with 'IF' is antecedent, and the statement associated with 'THEN' is consequent. The antecedent is the combination of various attributes $(A_1 - A_k)$ with their i_{th} linguistic variables $(S_1 - S_n)$ using logical operators like *AND*, *OR*, and *NOT*. Furthermore, the consequent statement associated with '*THEN*' is output O represented with a linguistic variable D. The output is a fuzzy variable that is again converted to a crisp number using defuzzification methods. The complete process is to employ the vague input variable to the fuzzy inference model, where the inference is made using the predefined set of rules and gives a fuzzy output that is converted to a crisp value using the defuzzification process. Another scenario of fuzzy set theory is when the input is a crisp number but converted to the fuzzy variable using the fuzzification process. In this process, each crisp input variable is associated with a linguistic variable using a membership function, as mentioned in (14).

$$F = \{(x, \mu_k(x)) : \forall x \in X\} \tag{14}$$

In (14), F represents the set of fuzzy variables for crisp input x, μ_k represents the membership function for the kth fuzzy variable within [0,1]. Further details about this method can be gained from the literature [64]. Since this method does not require any physical model or prior historical data, it is extensively used for fire and gas-related hazard mitigation in the UCM. In literature [50] fuzzy AHP-based Bayesian network is studied over the explosion hazard. Various factors like ventilation failure, seal quality, human error, and instrument error are considered, and a questionnaire was arranged with multiple subject domain experts to get the occurrence probability of those factors based on fuzzy AHP. Literature [19] presented the study in fire intensity for UCM. The concentrations of O_2, N_2, CO and temperature are considered as the input to the fuzzy inference system. The trapezoidal membership function is used for all the input for the fuzzification process, and the centroid of area (COA) has been used for the defuzzification of the fuzzy output of the model. In literature [54], fuzzy TOPOSIS-based hazard mitigation is proposed. It considered multiple hazard factors for the UCM like geochemical, electrical, mechanical, chemical, environmental, personal, and social. The ranking of the abovementioned factors is done using fuzzy TOPOSIS. Literature [7] also deals with fire intensity monitoring in the UCM based on various gases but using a type 2 fuzzy logic controller. The type-2 controller has the advantage of modelling the uncertainty in the membership function of the type-1 fussy controller. Similarly, the literature [13] and Shi et al. [86] presented the different variants of the fuzzy-based hazard monitoring system for the UCM.

4.6 Bayesian

It is another popular ML technique based on the probability theory. Primarily used in a network form, it is integrated with an acyclic graph to represent the complex and fuzzy relationship among the various factors of a given problem. These networks, also known as Bayesian network (BN), includes a directed acyclic graph and conditional probability table. Figure 2 depicts the basic structure of a BN. The joint probability distribution of a node can be calculated using (15).

$$P(a,b,c,d,e,f,g) = \prod_{x\in a,b,c,d,e,f,g} P(x|parent(x)), \tag{15}$$

where x represents the individual nodes and parent(x) represents the parent node of x. More details in this regard can be found in Stephenson [88]. The usage of BNs in UCM hazard mitigation has been extensively studied. Literature [90] has shown the usage of a BN integrated with the Delphi method as an effective tool for assessing mine explosion hazards. Zhang et al. proposed a gas outburst prediction model based on weighted Bayesian [106]. The posterior probabilities under various indexes are weighted based on the entropies among the indexes. The outburst probability is then calculated using the weighted posterior probabilities. In literature [49], Li et al. studied the fuzzy Bayesian network for the risk assessment of the mine ignition sources. A fuzzy AHP model is adopted to incorporate the decision of various subject experts based on their expertise, knowledge, education level, and other parameters. A similar kind of study can be seen in articles [23, 34, 47, 48].

4.7 Neural Networks

ANNs are biologically inspired mathematical models consisting of processing elements called neurons. Each neuron is connected using a coefficient called weight [84]. The fundamental structure of an ANN is depicted in Fig. 3. Unlike the previously discussed models, ANN does not require explicit modelling to exhibit the detection or classification task. Therefore, ANN is a suitable candidate for complex physical phenomena where mathematical modelling is not possible or is not resource-efficient. These supervised learning-based data-driven models are diverse based on their fundamental operation and architectures. For UCM gas hazard cases, neural networks are extensively used for forecasting and prediction purposes. These

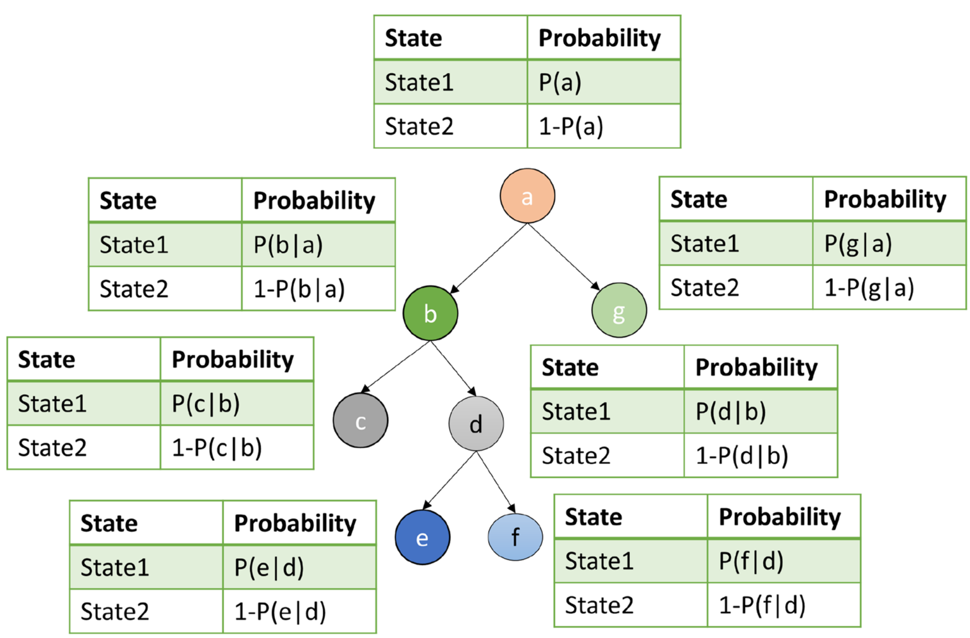


Fig. 2 Knowledge-based expert system

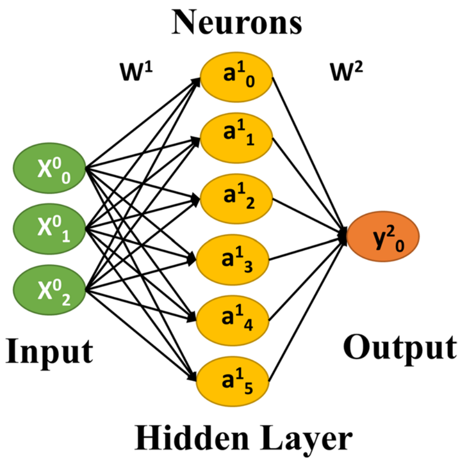


Fig. 3 ANN Architecture

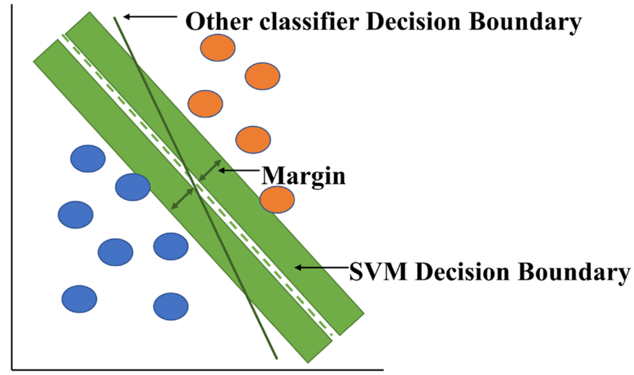


Fig. 4 ANN Architecture

models can broadly be classified into two groups, i.e., shallow neural networks and DNNs. Both types are briefly explained as follows.

1. Shallow Neural networks: A shallow neural network is a specific class of neural network model with a comparatively smaller number of hidden layers than a DNN. These models are considered less complex than DNNs like CNNs or recurrent neural networks (RNN). Support vector machines and ANN with a single hidden layer are popular models in this category. The basic structure of the Shallow neural network is shown in Fig. 3. The computational process associated with the model in Fig. 3 is as follows. The majority of the neural network model follows a fundamental computation process. This process is divided into two steps, i.e., forward propagation and backward propagation. The brief of these two processes is discussed below.

   (a) Forward propagation: The non-linear combinations of input weighted by dedicated coefficient and biases are joined together to achieve a required output value. A typical realisation of the forward propagation for a network in Fig. 3 is given in (16).

   $$A^1 = g\left\{ \left\{W^1\right\}^T \cdot X + B^1 \right\}, \tag{16}$$

   where A^1 is the activation of hidden layer '1', W^1 is the weight matrix associated with the hidden layer '1' and the previous layer, X is the previous layer input in vector form, B^1 is the bias associated with layer '1'. In (16), g, represents the non-linear activation function, like sigmoid, tanh and RELU. Similarly, the output can be realised as,

   $$Y_0^2 = g\left\{ \left\{W^2\right\}^T \cdot A^1 + B^2 \right\}$$

   (b) Backward propagation: It updates the weight or coefficient of each layer based on the gradient descent algorithm. The gradients of residual between the actual and the predicted values are derived and propagated back throughout the network. The residuals can be calculated using a dedicated loss function, given as,

   $$J = \frac{1}{2m} \sum_{i=0}^{m} \left(y_i - \hat{y}_i\right)^2 \tag{17}$$

   In (17), J is the loss function. The parameter W for the different layers can be updated using the gradient descent algorithm [77], and the parameter updates can be represented as follows.

   $$W = W - \alpha \frac{\delta J}{\delta W},$$

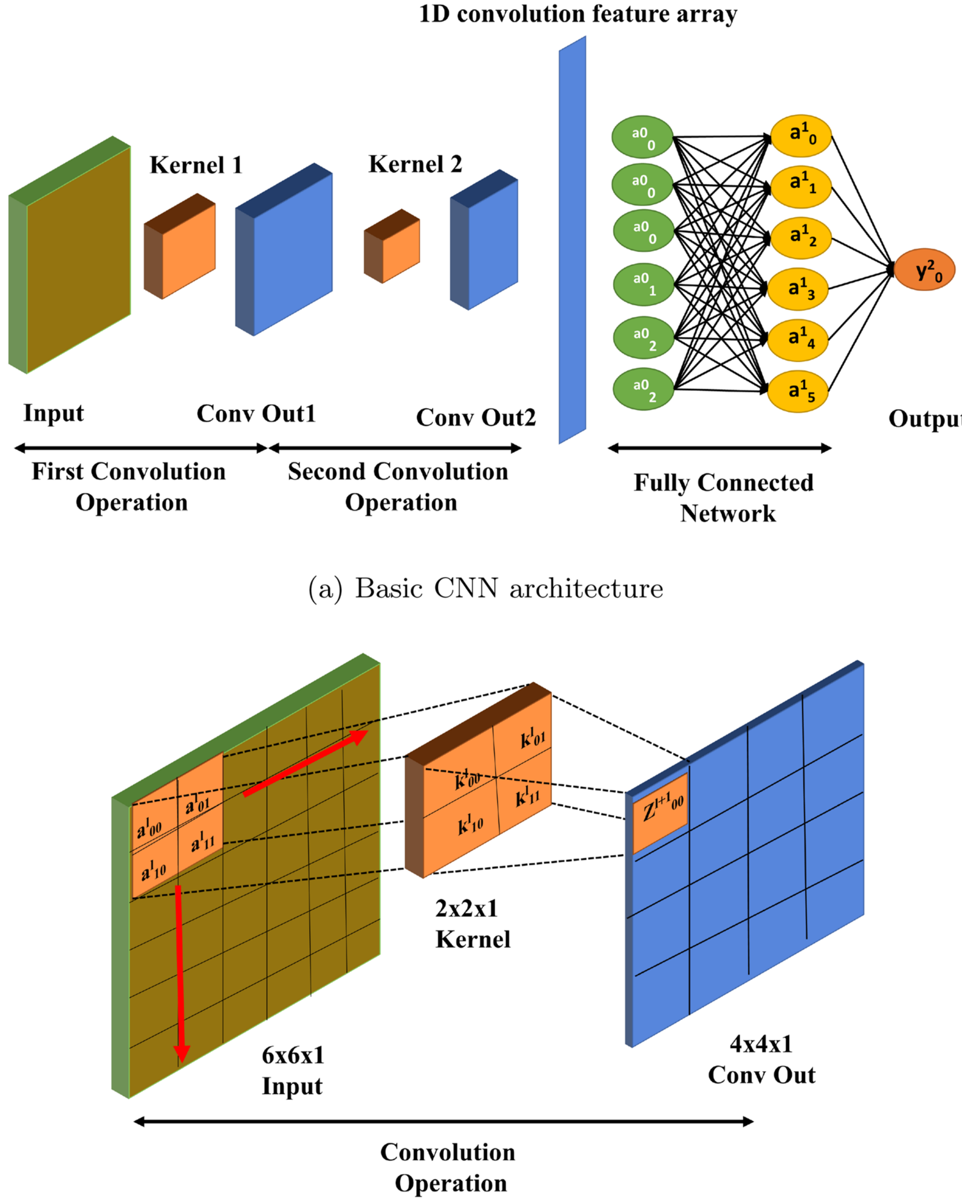
   where α is a hyperparameter called learning rate, $\frac{\delta J}{\delta W}$ is the gradient of the loss function with respect to the parameter W. The capability of ANN in generating non-linear decision boundaries helps to model problem solutions for complex tasks.

In contrast, SVM, a large-margin classifier, is different from the traditional ANN models in terms of its decision boundaries. SVM implements an extra margin around the decision boundaries, shown in Fig. 4, which is uncommon in the ANN-based models [63]. Therefore, SVM provides more accurate decisions as compared to the ANN-based classifiers. These models are considered for gas concentration prediction in UCM scenarios. The study in the literature [100] introduced the backpropagation ANN (BP-ANN) model to mitigate the danger degree associated with spontaneous coal combustion in the UCM. The authors also investigated the genetic algorithm's effect to optimise the model's hyperparameter. The outcome of the complete study was an optimum and robust model with faster training performance. An Unscented Kalman filter (UKF) based BP-ANN model is introduced in the literature [102]. The UKF is claimed to be used to adjust the BP-ANN model parameters, but no such validation is shown in the literature. The author also claimed that the proposed system is robust against faults and has high decision-making precision. Authors of the literature [94] have proposed a multi-layer-perceptron model for the methane concentration prediction of UCM. They studied the effect of the various architecture in the prediction process to forecast the methane concentration for the next 15 min. Literature [6] has proposed an ANN model to classify the fire hazard class using the measurable parameters of UCM like CO, CO_2, O_2, air velocity, and other parameters. The study has shown that the proposed model's classification accuracy was 97%. Similar kinds of studies like [32, 37, 78, 101] suggested the application of ANN as a reliable model for gas hazard prediction in the UCM scenarios. In contrast to the studies involved in ANN, a significant portion of the literature also involves SVM-based models. The article [20] has proposed an SVM-based regression model integrated with particle swarm optimisation (PSO). The model was intended to predict the temperature of the continuous coal combustion inside a goaf using the present gases like CO and CO_2. In comparison with the BP-ANN models, the SVM-based regression model was more accurate in temperature prediction. The literature [46] has investigated the systematic comparison of the Random Forest model and SVM for the prediction of the temperature of continuous coal combustion in UCM. The principal component analysis was used to generate a dimensionally reduced feature set. The investigation has shown that the performance of SVM can be significantly affected by the selection of the hyperparameter, but in comparison, the RF model was robust against the proposed SVM and showed better prediction accuracy compared to the SVM. However, an optimum selection of the SVM hyperparameter significantly improves the prediction performance of the SVM. Another study in the literature [92] has compared K-nearest neighbour (KNN), Logistic regression (LR), Decision-Tree (DT), and SVM for the mine hazard classification. For this purpose, 17 input variables affecting underground safety were selected. The input attributes like mean, variance, quartile, and maxima are manually extracted for each input variable. The comparison has shown that, except for the DT, all models have shown acceptable classification performance based on the accuracy and F1-score metrics. Apart from the normal SVM, one of its variants, i.e., least square-SVM (LSSVM), has also been the subject of discussion in the field of UCM gas hazard. One study in the article [15] has investigated the methane-based gas-related hazard using LSSVM. The authors have proposed a forecasting and forewarning model based on the LSSVM. The forecasting model is claimed to have high precision with a credible forewarning model. However, the proposed model was not compared with the other available methodologies that could have supported the claim. Other similar studies based on the investigation of LSSVM for UCM hazard scenarios are presented in the literature [18, 104, 107].

2. DNN: Unlike shallow neural networks like ANN and SVM, DNN architectures consist of a larger number of hidden layers and usually have a complex neural network. ANNs with a relatively higher number of hidden layers, also called Deep-ANN (DANN), Convolutional Neural Networks (CNN), and RNN, are among the most studied fundamental DNN models. The operational fundamentals of the DANN are the same as ANN, except it has a larger and more complex network structure. However, the operation of CNN and RNN has fundamental differences compared to the DANN. The basic principle behind CNN and RNN are discussed below.

    (a) CNN: These models are commonly employed for spatial feature extraction. The auto feature extraction capability of the CNN models has an additional advantage over the other DNN models where manual feature extraction is required [3]. The basic structure of a CNN architecture is shown in Fig 5. In contrast to the ANN architecture, CNN performs convolution operations between the input and the kernel. The input block is a tensor of shape $(h \times w \times c)$, where 'h' indicates the number of rows, 'w' indicates the number of columns, and 'c' represents the number of channels. The kernel block is analogous to the neurons of ANN architecture, containing specific weights that can convolve across the input. The kernel block is also a tensor having the shape of $(a \times b \times c)$, where 'a' is the height of the kernel, 'b' is the width of the kernel, and 'c' is the number of channels. It is worth mentioning that the number of channels of the kernel and the input shall be the same. The 'Conv out' block represents the tensor that stores the extracted features from the convolution process. For more details in this context, literature [29] can be taken as a reference. Although the ML-based models for the UCM scenarios are at the initial stages of the research, CNN-based gas outburst prediction models are also available. The literature [51] proposed a CNN-based coal and rock outburst hazard

Fig. 5 CNN-based model



(a) Basic CNN architecture

(b) Convolution Operation

using acoustic emission (AE) and Electromagnetic radiation (EMR) signals. The AE and EMR signals are initially modified using empirical mode decomposition (EMD) and then converted into a two-dimensional tensor for the CNN input. The authors have used an indirect method of predicting the rock and gas outburst, i.e., using EM and EMR instead of gas concentrations. In the literature [105], RFID based methane concentration prediction model is proposed. The prediction algorithm is based on an integrated CNN-LSSVM algorithm. The CNN is used to extract the robust features from the row sensor data using an RFID tag, and the prediction is made using the LSSVM model. The authors of the literature [73] have established the gas hazard classification and prediction model using K-NN integrated with CNN. The K-NN is used to classify the source of abnormal gas concentration, and CNN is used to predict the outburst risk due to the blasting process.

(b) RNN: These are like the ANN in architecture with some additional temporal structure. This temporal structure extracts the temporal features of any time series sequence. The basic architecture of the RNN is depicted in Fig. 6. In the RNN architecture, X_1-X_T represents the time series data

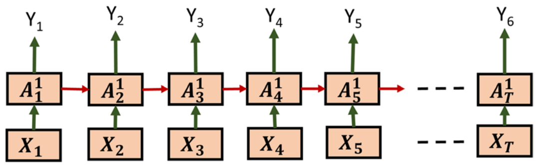


Fig. 6 Basic RNN architecture

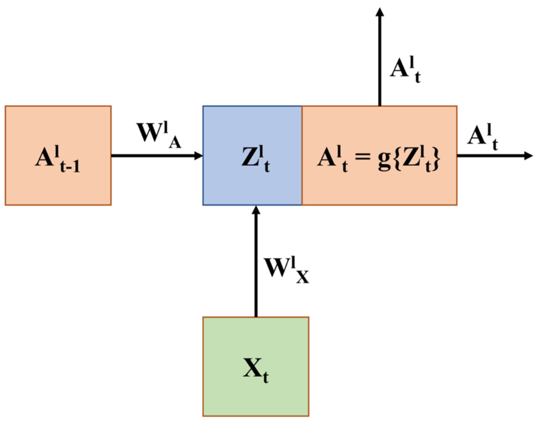


Fig. 7 RNN cell

sequence, and A_1^1-A_T^1 are the extracted features for the given time-stamp $1 - T$. The subscript in the above-mentioned notations indicates the time stamp, and the superscript represents the layer number. Furthermore, the intuitive block diagram for one of the time-stamp operations in the RNN architecture is shown in Fig. 7. The RNN cell shown in the figure has two inputs, one is from the actual input (X_t) of the corresponding time stamp, and another is from the previous time-stamp (A_{t-1}^l). The other variants of the RNN are gated recurrent unit (GRU) and long short-term memory (LSTM). The basic difference between the plain RNN, LSTM, and GRU is that they exhibit memory-retaining cells operated by some gated mechanism. This memory cell helps to maintain the temporal features over the long temporal samples. The detail about the RNN models and their variants can be seen in the literature [79]. The usage of the RNN-based models for the coal mine methane concentration forecast is evident in recent literature. The article [103] presented the LSTM-based menthane gas concentration prediction in the UCM. The whale optimisation algorithm was used to optimise the LSTM for the hyperparameters. Additionally, the author introduced the input sequence's empirical mode decomposition (EMD) to get individual intrinsic mode function (IMF) as an input to the LSTM. The authors in the literature [45] proposed uniform manifold approximation and projection (UMAP)-LSTM-based mine fire prediction using various attribute gases like O_2, CO, CO_2, CH_4, H_2, N_2, and C_2H_4. The proposed model was substantially efficient compared with traditional ML methods like SVM and ARIMA. The studies in the literature [61] and Dey et al. [22] also utilise the LSTM -based model for gas hazard prediction in the coal mines.

Apart from the CNN and RNN models, some literature, like Dey et al. [21] and Hati et al. [31], advocate using a hybrid CNN-LSTM model for gas concentration forecasting in coal mines. The hybrid architectures leverage the advantages of both, i.e., auto feature extraction from CNN and maintaining the temporal integrity between the extracted features. These hybrid models have shown better performance than the independent CNN or RNN models.

4.8 Comparison of Fusion Models

This section compares the above-mentioned algorithms in the context of UCM scenarios. This attempts to filter out the most suitable sensor fusion algorithms for the UCM scenarios. The comparison is presented in Table 4.

Considering the UCM scenarios, the dynamic and complex environment makes it difficult to realise a physical model for a gas hazard monitoring process. Even the studies in the literature, like Wu et al. [99], are based on the approximate physical model with several assumptions. No practical usage of physical model for gas hazard prediction and mitigation has been reported yet. Therefore, the physical models are not suitable for the gas hazard prediction task. Due to the non-linear relationship among the gas concentrations and their hazards, maximum likelihood and least square-based models are also unsuitable for the concerned purpose. Therefore, very little literature can be found for the Kalman filtering, least square, or Maximum likelihood.

Compared with the previous models in Table 4, the Bayesian model is not bound to any predefined mathematical model as in the least square or maximum likelihood. In contrast, these models require conditional probability tables that may be cumbersome to design for multiple hypotheses and conditionally dependent events. Although, all these models severely suffered from data uncertainty and vagueness. In contrast, the tough and dynamic environment makes sensor-based monitoring susceptible to various noisy measurements that impose uncertainty on the data. Fuzzy-set theory and

Table 4 Comparison of UCM gas monitoring models

Model	Advantage	Disadvantage
Kalman filtering [99]	1. More accurate compared to data-driven models	1. Kalman filtering is only suitable for a well-defined physical model
	2. It effectively considers the process model and measurement model noise, shown in (2) and (4), which is not present in the other traditional approaches	2. Non-linear process models are complex to realise, and those are computationally expensive
Least Squares [81]	1. Simple modelling	1. Require a predefined model, unsuitable for a dynamic and complex process
	2. No requirement for prior information	2. Not flexible towards the changes in the input parameters
	3. Does not require any physical models	
Maximum Likelihood [4]	1. The usage of PDF instead of curve fitting improves the estimation accuracy	1. Requires prior knowledge of the PDF related to the parameters under investigation
	2. It does not require any physical model	2. Estimates can be biased for a small sample
		3. The complexity of the model depends upon the choice of the likelihood function
Bayesian [23, 34, 47–49, 90, 106]	1. Does not require any physical model	1. A priori probability distribution is required beforehand
	2. Suitable for the small data sample	2. For multiple hypotheses and multiple conditional dependents, it becomes complex
	3. Combining different sources of knowledge [96]	3. Require conditional probability tables for Bayesian network models [40]
		4. Considers only two hypotheses at a time
Knowledge-based expert systems [25, 36, 68, 76, 80, 85, 87, 108]	1. Simple in design	1. Requires predefined rule base
	2. No need for any physical models	2. Can not handle uncertainty in measurement
		3. It May result in a faulty decision when slight observation deviations occur
Fuzzy set theory [7, 13, 19, 50, 54, 64, 86]	1. Can effectively handle vagueness in the data sample	1. Require a predefined rule base
	2. Type-2 fuzzy inference model can handle data uncertainty [58]	2. Only supports the identification or classification tasks, not suitable for forecasting [1]
	3. No requirement for physical models	
Neural Networks [6, 15, 18, 20–22, 31, 32, 37, 45, 46, 51, 61, 73, 78, 79, 92, 94, 100–105, 107]	1. It Does not require any explicit physical model	1. The feature engineering step can be time cumbersome
	2. Learns the rules related to a process using historical data only	2. These are black-box models [30]
	3. Does not require any prior knowledge of probability distributions [55]	3. These models are computationally complex compared to the other models

Dempster-Shafer-based models can handle these uncertainties and vagueness in the data. These models are found significant when very small information is available, and the inference engine is developed with the help of a human expert and cognitive intelligence. However, these models are not suitable for pattern recognition or forecasting tasks. Unlike the other sensor fusion algorithm, ANNs and DNNs can find the non-linear relationship between any process's input and output variables. These models proved to be highly efficient for highly complex and non-linear processes.

Moreover, shallow neural networks like ANN or SVM are susceptible to noisy data, but DNN models like CNN can handle the noisy data. Neural networks' efficient pattern recognition capability makes them a suitable for the UCM hazard recognition models. The significant limitations of these data-driven models are observed when any fault in the sensor occurs. A faulty sensor may result in faulty observations resulting in faulty estimation or prediction. There is no literature found dealing with this practical issue. Additionally, most of the studies are primarily concerned with designing a data-driven model whose reliability may be a concern in uncertainty scenarios.

4.9 Comparison of Neural Networks Models

A brief comparison of the conventional neural networks-based models from the existing articles in the UCM scenarios is presented in Table 5,

Table 5 evaluates the usage of ML models related to gas hazards in the UCM. The table dictates the significant performance of these models in terms of accuracy in a dynamic and complex environment of a UCM. Most of the models presented in the discussion have achieved good classification or regression accuracy.

4.10 Challenges Associated with Neural Networks

The models discussed in Table 5 access the sensor data from the underground coal mines to process inferential actions. The complete inference pipeline exhibits data collection, data engineering, model preparation and model deployment. In the data engineering step, features from the row sensor data are extracted and normalised for training and validation purposes. However, certain limitations associated with this approach are as follows,

1. A very small number of articles are available for DNNs implementation in UCM hazard monitoring.
2. All the hazard forecasting models adopted a uni-model approach, i.e., individual networks are dedicated to

Table 5 Comparison of neural network in UCM scenarios

Model	Literature	Task	Purpose	Remak
ANN and its variants	[100]	Classification	Prediction of coal spontaneous	No quantitative result is mentioned
	[102]	Regression	Coal and methane outburst prediction	R^2—0.99
	[94]	Regression	Prediction of methane concentration	Mean Test RMSE—0.021, MAPE%—2.05
	[6]	Classification	Mine fire classification	Accuracy—97%, F1-score—96.7%
	[78]	Classification	Coal and gas outburst prediction	Classification accuracy 87%
	[32]	Classification	Coal and gas outburst classification	Accuracy—100% approx
	[101]	Regression	Gas outburst prediction	MSE—393, R^2—0.98
	[37]	Regression	Mine environment index prediction	MAE—0.15, RMSE—0.21, R^2—0.6654
SVM and its variants	[20]	Regression	Coal temperature prediction	MAE—0.5976, RMSE—0.8852, R^2—0.9656
	[46]	Regression	Coal temperature prediction	MAE—0.461, RMSE—0.797, R^2—0.9709
	[92]	Classification	Multiple hazard classification	Jaccard—0.92, F1-score—0.89
	[15]	Classification and Regression	Methane concentration forecasting and hazard classification	The relative error between the actual and predicted values is between 0.088 and 6.915%
	[107]	Regression	Mine gas prediction	No quantitative result is mentioned
	[104]	Regression	Gas content prediction	The relative prediction error is 0.39 to 1.71%
	[18]	Classification	Seismic hazard prediction	Prediction accuracy 93.96%
CNN and its variants	[51]	Classification	Coal and gas outburst prediction using AE and EMR	Accuracy—98%
	[105]	Regression	Methane gas density prediction	High accuracy (quantitative result is not published)
	[73]	Classification	Outburst risk prediction	Accuracy—86.1%
RNN and its variants	[79]	Regression	Coal mine gas prediction	MAE—0.018, RMSE—0.025
	[103]	Regression	Coal mine gas concentration prediction	RMSE for O_2, CO, CH_4, CO_2, H_2, N_2, and C_2H_4 gases—0.288, 0.006, 0.0995, 0.902, 0.238, 0.452, and 0.006
	[45]	Regression	Methane concentration prediction	Highest R^2—0.92 and Lowest RMSE—0.02
	[61]	Regression	UCM gas prediction	Prediction accuracy—89.7–92.4%
	[22]	Regression	Concentration forecasting of UCM gases	Lowest MSE—0.029
Hybrid of CNN and RNN	[21]	Regression	Miner's health quality index (MHQI) prediction	MSE—0.0009
	[31]	Regression	Prediction of ventilation system airflow of UCM	RMSE—0.01, MAE—0.02, Accuracy—96.7

individual parameters for the predictions. However, the prediction of that parameter can be influenced by other factors which are not considered in any of the present literature.

3. Actual sensor data usually have uncertainty due to various factors. Any uncertainty may lead to wrong classification or estimation, especially in edge scenarios, e.g., a methane sensor with a reading of 12,000 ppm, a threshold value of 12,500 ppm and a measurement uncertainty of 5% may not be able to decide whether the sensor observation is below the threshold or above it.
4. All the neural network models are trained on a crisp sensor value that does not consider the sensor uncertainties, which may result in reduced accuracy in real-time scenarios.
5. The issue can persist if there is an occurrence of sensor malfunctioning. Due to the harsh and complex underground environment, sensor malfunctioning is frequent and inevitable in the UCM. The evidence of faulty node scenarios has been observed in the UCM hazard monitoring studies. The study in the literature [82] prevailed about a malfunctioning methane sensor on the third day of their experiment in the coal mine. Consequently, the methane concentration was high compared to the other methane monitors. Another study in literature [42] also reported a similar kind of event. The methane monitor installed at the 80th shield gave conflicting observations compared to the other methane monitors. A malfunctioning sensor observation may result in an out-of-distribution (OOD) scenario, and it can be easily handled using some statistical anomaly detection methods. However, it is not always necessary to observe a malfunctioning sensor following OOD. If such occurrences happen, the estimation or classification process suffers from a significant reduction in accuracy.
6. The dynamic and complex UCM environment imposes many restrictions on traditional hazard monitoring systems. Based on the survey of various works of literature, the significant challenges associated with coal mine sensor networks are as follows.

   (a) On the completion of coal extraction in one of the mine galleries, there is a requirement to move the whole machinery and infrastructure to the following operating region. This dismantling and remounting process imposes limitations on conventional wired communication infrastructures.
   (b) Moreover, wired communication networks are prone to mechanical and other damage.
   (c) In this scenario, wireless infrastructure is advantageous in terms of flexibility and portability. However, the subsurface operations of the UCMs put restrictions on traditional wireless systems.
   (d) Additionally, these wireless systems face high signal attenuation due to the coal dielectric properties and UCM geological features.

5 Possible Solutions

The unreliability in the sensor observation due to node or network-initiated malfunctions can be avoided using a Dempster-Shafer evidence theory (DSET)-based multi-criteria fusion process. The missing data and uncertainty-handling capability of DSET confirm it as a reliable decision-making model [27]. Due to its superior uncertainty handling capability [8], DSET is widely used in various fields like wireless sensor networks, fault detection in motors, and environment monitoring [2, 35, 57, 67]. However, the DSET has not ever been investigated in the UCM environment monitoring process that inherently poses significant noise in real-time sensor observations. Therefore, there is an opportunity to investigate the DSET for the UCM scenario. However, DSET combines the beliefs from multiple sources to make a decision. Therefore, increasing the number of sources would lead to an increase in computational cost. Therefore, DSET can not replace the neural network that can handle a large amount of information simultaneously. However, DSET can be utilised as a front-end to the conventional neural network models, utilising fixed and comparatively lesser data to identify and filter out malfunctioning sensor observations. The utilisation of DSET for sensor fault identification has been studied in the literature [28]. The literature shows a remarkable improvement in decision-making compared to conventional models.

Another significant challenge is reliable communication. The limitations of wired and wireless communication infrastructure have already been discussed. Due to the challenging geography of UCM and the nature of the underground environment, realising a reliable wireless sensor network is inefficient. Therefore, the implementation of any real-time gas hazard monitoring model is strictly limited due to the implications mentioned above. The conventional deep learning (DL) models require higher computational resources like cloud-based servers or a dedicated computer. Therefore, these models cannot be directly implemented for UCM in real-time scenarios. Although the local area wireless sensor networks, where line of sight communication is possible, like in longwall mining operations, can be adopted, these local area networks can be integrated with the wired communication infrastructure. LPWAN is sought as an optimal solution for developing a Local area network, given their low power and long-range features. Another approach is edge machine learning (EML), where a neural networks can be transformed into a lighter version based on the requirement of the resource constraint edge devices like microcontrollers

[62]. The EML models can run on edge devices and can be deployed directly on the actual (in-situ) location. Therefore, it does not require any internet connection, reducing network-related latency and security issues.

6 Conclusion

The underground coal mine environment is utterly unpredictable due to the sudden presence of various gas hazards and therefore requires monitoring continuously for workers' safety. This literature survey discusses the challenges observed for the end-to-end realisation of the UCM gas hazard monitoring system. The survey prevails over certain limitations associated with the commonly adopted gas monitoring models in terms of scalability, human intervention and prediction and classification accuracies. Moreover, neural network-based models have performed significantly well in terms of estimation and identification accuracy. However, the reliability of these models is challenged by the data uncertainty originating from real-time sensor observations. Additionally, the implementation of neural networks traditionally employs a cloud server or dedicated computer, but the implications of WSN limit these approaches.

Therefore, based on these existing limitations, a multi-sensor fusion based on DSET can be used as a front end of the neural network to filter out faulty and malicious data samples in real time. Since traditional cloud-based neural network solutions are not feasible, EML can be a better solution for practically implementing the smart hazard prediction model. Although this study is limited to the review of the ML-based gas hazard identification methods, this can be further extended to the other hazards to achieve a broad idea in the context of overall UCM hazard safety.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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