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Safety Analysis Improvement in Fire Risk Assessment Model and Optimized Risk Indexing using Deep Learning Approach

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Abstract: Gas pipeline risk assessment is crucial due to many dangers and financial losses. The findings are more accurate and reliable when deep learning is used. This study's objective is to assess pipeline fire, explosion, and hazardous gas release risks using an Efficient Deep Learning Model (EDLM)-optimized risk indexing procedure. Deep Recurrent Neural Network (DRNN) and the Ebola Optimization Algorithm are combined to create the proposed EDLM (EOA). EOA is used in the DRNN to facilitate the weight update process. Utilizing MATLAB software, the evaluation of the fire risk was finished. Using EDLM process analysis, the weight of each fire risk indexing was added up, and the fire risk level was determined using a five-state criterion system that comprised highly unpleasant, greatly desirable, favourable, moderate, and unfavourable. The ultimate risk score for a fire, explosion, and poisonous gas leak in a gas pipeline in Korea is in a favourable range. The fact that there are many different variables that might cause a fire and that they don't happen very often is proof positive of this result. To improve the accuracy of fire incidence, an efficient deep learning model is given. Furthermore, the fire risk indexing model is built upon the fire prediction model. The proposed method is put into practise and contrasted with traditional approaches like recurrent neural networks (RNN), artificial neural networks (ANN), and support vector machines (SVM), in that order. Consequently, it is expected that safety managers will find the results useful in making decisions on the risk management of gas pipelines.

Keywords: *deep learning model, fire risk assessment models, industry, deep recurrent neural network, Ebola optimization algorithm and optimized risk indexing.*

1. Introduction

In the process industry, risk assessment techniques are used to not only identify possible accident situations but also to analyse and implement the appropriate safety measures and equipment to prevent or lessen them [1, 2]. These safety measures and activities are referred to by a number of terms, such as safety barrier, layer of protection, and countermeasure. Each of these terms refers to a technique, either non-physical or physical, intended to prevent, reduce, or minimise unfavourable events or accidents [3]. Monitoring the effectiveness of these safety barriers is becoming increasingly important. Process safety is a methodical strategy that guarantees the integrity of systems and operational processes handling hazardous materials. Process safety, as opposed to occupational safety, which focuses on risks that could result in health issues, focuses on the avoidance and mitigation of process hazards that could lead to the release of chemicals or energy (such as slips, trips, and falls). In the long run, these hazards may be detrimental to human health, the environment, productivity, and resources [4].

One of the most harmful incidents that might occur is fire, particularly in facilities that handle a lot of hazardous products. In contrast to other mishaps, like explosions, flames may linger for a while and the thermal radiations they create add up to something [5]. At the same time, a connection that needs some work is the intensity of target entities under the effect of hot radiation. The fire-induced cascade effect is a potent cycle because of these characteristics [6]. Emergency workers may arrive at the fire site during a fire crisis response at various times, putting them in a variety of emergency scenarios [7]. There aren't any refinery-specific fire risk assessment techniques that the authors are aware of. An older strategy is to utilise one of the various processes hazard analyses (PHA) methods that are often used in the process sector. The most well-known of these methods include risk file approaches, checklists, Hazard and Operability Study (HAZOP), failure modes and effects analysis (FMEA), and risk file approaches [8]. Quantitative techniques like fault tree testing (FT) and Layer of Protection Analysis (LOPA) are frequently used if it is believed that the effects of PHA require additional justification [9]. Despite the positive dedication to overcoming hardship and the intended use of these strategies, there are significant limitations that prevent their use in more complicated contexts, such as those including many important and dynamic KPIs.

As Deep Learning (DL) [10] gains traction in various technical domains, including the process industry, more and more relevant research is being done on the subject. Industrial applications have been estimating the fire risk

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assessment method using DL methodologies in recent years. The fire risk assessment approach can be built using a variety of deep learning (DL) techniques, including ANN, SVM, fault tree analysis (FTA), event tree analysis (ETA), decision trees (DT), deep neural networks (DNN), deep belief neural networks (DBNN), and others. The performance of DL is further enhanced by utilising optimization techniques including the Whale Optimization Algorithm (WOA), Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO), Firefly Algorithm (FA), and others.

Main contribution of the article

- The goal of this research is to create an EDLM for optimum risk indexing and fire risk assessment. DRNN and EOA are combined to create the proposed EDLM. With the help of EOA, the DRNN's weight update procedure is accomplished.
- At first, real-time data is gathered from Korean fire incidents. Under typical conditions, the current fire prediction models do not offer appropriate levels of accuracy.
- The fact that there are many different elements influencing fire occurrence and that fires occur rarely serves as validation for this result. In order to improve fire occurrence accuracy, an effective deep learning model is presented.
- Furthermore, the fire prediction model serves as the foundation for the development of the fire risk indexing model. The proposed method is put into practise and contrasted with more traditional methods like RNN, SVM, and ANN, in that order.

This essay's remaining sections are arranged as follows: Relevant research on fire risk assessment techniques is covered in section 2. A thorough description of the suggested methodology is given in Section 3. Section 4 provides an explanation of the proposed technique's outcome evaluation. In section 5, the article's conclusion is provided.

2. Literature Review

Researchers have created many methods for assessing the danger of fire in industry. This section reviews just a few works.

Fuzzy FTA and ETA are two tools that Hosseini et al. [11] propose for a cost-based fire risk assessment in the natural gas sector. The pathways leading to an outcome event would be graphically depicted using FTA and ETA. A case study of the South Pars gas complex processing plant was used to apply the paradigm. A process hazard assessment identified the primary root causes of fire incidents in gas processing facilities (PHA). Based on the inaccurate assessments of experts, fuzzy logic has been applied to determine the probability of fundamental occurrences in FTA.

Xie et al. [12] enhanced the multi-sensor fusion technique by utilising the cloud model and the Jensen-Shannon divergence theory to produce an oil storage risk assessment. Following the discovery of the key accident evaluation components and associated threshold intervals of varied risk levels, the fuzzy cloud membership functions (FCMFs) corresponding to different risk levels were built. After processing the sensor monitoring data using the FCMF's correlation measurement, basic probability assignments (BPAs) were generated utilising the risk assessment frame of discernment. The degree of accident risk was assessed following the enhanced evidence fusion model's pre-processing of the BPAs. A case study was conducted utilising the monitoring data in order to evaluate the probability of accidents involving vapour cloud explosions (VCEs) caused by leaks in liquid petroleum gas (LPG) tanks.

To avoid and reduce the risks associated with storage fires, Ding *et al*. [13] have suggested a risk-based safety measure allocation. Relevant safety precautions are discussed, and their effectiveness in lowering the danger of storage fires is examined. As a case study, a big storage fire accident is applied using the methodology and the generic framework, and the likelihood of a fire accident and its repercussions are greatly decreased, demonstrating the effectiveness and applicability of the suggested approach.

An enhanced quantitative risk assessment of a natural gas pipeline that takes high-consequence zones into account has been published by Yin et al. [14]. First, we create two models: a risk consequence model with potential direct and indirect losses derived from the likelihood of disaster advancement, and a failure probability model based on better historical failure and catastrophe derivation probabilities. Above-discussed hidden phenomenon of high-consequence sites may be successfully prevented by addressing the loss of life value in accordance with population density. This approach takes into account both the Chinese societal concept of "life comes first" and the equality of human rights. This revised approach is used to assess a pipeline situated in China.

An Analytic Hierarchy Process (AHP) and Fuzzy Comprehensive Evaluation (FCE)-based risk assessment of oil and gas pipeline hot work has been proposed by He et al. [15]. It might assist pipeline businesses in managing the risks associated with hot work and enhancing pipeline safety. This essay assesses the danger of a single hot work in the spring of a single pipeline in a high consequence zone using a single natural gas pipeline in China as an example. The work safety analysis is first used to evaluate the risk variables (JSA). Following that, experts were contacted by completing a questionnaire.

3. Proposed System Model

Create a fire risk model in this study by taking optimum risk modelling and deep learning into account. The explanatory variables (A) that influence the presence of response variables (B) and fibre are contained in the input database linked to the fire risk. The frequency of fire occurrence is indicated by this response variable. In this study, EDLM is created to determine the presence of fire in industry. Figure 1 depicts the entire architecture of the suggested methodology.

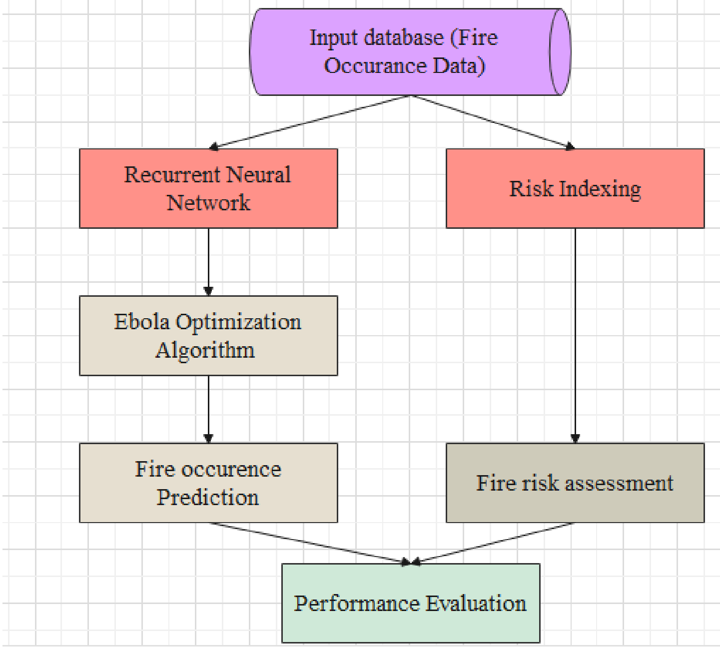

Fig 1: Proposed Architecture of Fire Risk Assessment

Initially, input data is collected from the online sources. After that, the data is utilized to fire occurrence prediction by using RNN and EOA. Additionally, the risk indexing is proceeding for fire risk assessment process. Lastly, statistical measures are used to assess how well the suggested fire occurrence prediction outcomes work. Among deep learning systems, the response variable often consists of frequency data and uses the count information analysis technique. Binomial and Poisson distributions are thought to be applied to the analysis of discrete probability distributions in order to validate the fire occurrence data. Since the binomial distribution function is an industry-specific model that concentrates on the risk of fire in the oil and gas company, it is employed in the suggested strategy. When B is defined as follows, the random variable B can be distributed to a binomial function with N and P.

$$P(B = y) = \binom{N}{y} P^y (1 - P)^{N-y} \quad y = 0,1,\dots,N \tag{1}$$

Here, P can be described as the probability of success and N can be described as probability of success. The variance ($var(B)$) and expectation ($E(B)$) of B can be NP(1-P) and NP respectively. Y consists of binary data parameter such as o is described as no occurred fire and 1 is described as occurred fire. Here, EDLM is developed for forecasting fire risk in industries. The detail explanation of the EDLM is presented as follows,

3.1. Recurrent Neural Network

The RNN is an efficient network which considers precedent information in a closed loop. It can be repeated by merely communicating the intermediate state as input or network output. In instance, the input data [16] is integrated with the upcoming step. This type of network can be suitable while short term dependencies and it related on other in addition it did not operate for long term dependencies computed in compression. For this type of network, there are problem in training process, so by reproduction it can explode or disappear. To manage the limitation, this work utilized an EOA.

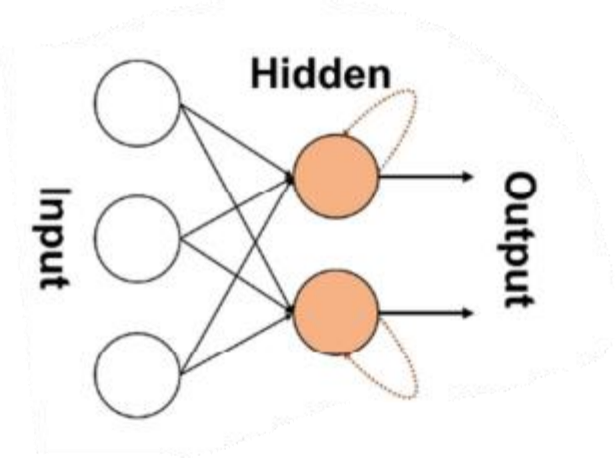

Fig 2: Simple RNN architecture

The RNN is one kind of ANN in which a directed cycle is created by the connections between the units. The network consequently gains an internal state that allows it to provide dynamic temporal features. Unlike feed forward neural networks, RNNs employ their internal memory to understand random sequences of inputs, as shown in figure 2. The primary RNN information can be obtained from the sequential data. In a typical neural network, all of the inputs are assumed to be independent of each other. Furthermore, this assumption is not given an efficient one in diverse situations. RNNs are recurrent structures that repeat a process for every element in a sequence, with the final computations determining the relationship between the results. The memory in the remaining advantages of RNN gathers data regarding the computations that have been made thus far [17].

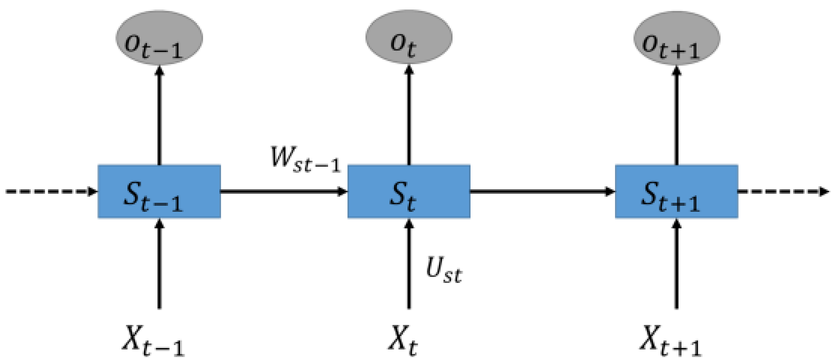

Fig 3: RNN with training process by hidden layers

The above figure 3 is a conventional structure of RNN.

Here,

O_t can be defined as the output condition at time t.

S_t can be defined as the hidden state throughout the time interval t.

X_i can be defined as the time period t

It offers the RNN training procedure in the network connection in its entirety. The RNN can be unrolled to display the network in its entirety in a sequential style. It is important to remember that the network memory and the concealed state at that moment are both shown in the graphic. It can be calculated using the input at this phase, which is given as follows, and information from earlier hidden states.

$$S_t = F(u_{Xt} + w_{st-1}) \quad (2)$$

Since the beginning value is taken to be zero in this case and $st{-}1$ can represent concealed state information, F can be thought of as a nonlinear function. Usually, the RNN model is trained using the Levenberg-Marquardt (LM) technique to increase convergence throughout this process. The effective convergence rate in the neural network mode helps improve the training procedure. Researchers have typically used the LM algorithm, which is similar to the Newton technique, to train their models. The training variable's efficient results are not produced by this training technique. Therefore, the EOA is used in this suggested technique to choose the ideal weight parameters in the RNN structure. The section below provides an explanation of EOA's entire architecture.

3.2. Ebola Optimization Algorithm

Ebola infections, commonly known as Ebola virus sickness, suggest exploitation of the host when they successfully stain the host (EVD). They belong to the family of viruses called Filoviridae, which is distinguished by a range of short to big filaments that have a maximum of 14,000 nanometres in length. Six distinct forms of EBOV are believed to exist. Notable events or epidemics in Africa include the Ebola-Zaire outbreak, the Tai Forest outbreak, the Sudan outbreak, and the Bundibugyo outbreak [18]. When a human is exposed to an infection through pathogen experts or contaminated environments, the disease spreads faster from that area and reaches a population level. The development and spread of illness are accelerated when in close contact with an infected person. This interaction requires the presence of skin breaks or mucous membranes in the mouth, nose, eyes, or other orifices.

- ❖ The SEIR-HDVQ model's performance served as the foundation for our EOSA algorithm design. The following procedure is used to formalise the EOSA algorithm: For each of the following scenarios, specific amounts (individuals and parameters) need to be established: Quarantined (Q), hospitalised (H), susceptible (S), infected (I), recovered (R), died (D), vaccinated (V), and (Q).
- ❖ Generate the case (11) index at random from people who are vulnerable.
- ❖ Determine the index case's fitness value by setting it as the current and global best.
- ❖ As long as at least one individual is infected and the number of iterations is not reached, each vulnerable person constructs and updates their position based on displacement. A quick displacement denotes exploitation, but a lengthy displacement suggests investigation. Keep in mind that moving an infected case increases the number of infections.
- ❖ Create new infected people (nI) according to (a).
- ❖ Include the newly created cases in I.
- ❖ Determine how many people should be added to H, D, R, B, V, and Q based on the size of I using the relevant rates.
  - o According to nI, modify S and I.
  - o Choose my current best and contrast it with the worlds finest.
  - o Return to step 6 if the termination condition is not met.
- ❖ return all solutions and the global best solution.

The secret person's level of refreshment is introduced at the lowest level.

$$mI_T^{t+1} = mI_i^t + PM(I) \quad (3)$$

The population-planned growth rate in this case is represented by $m\ (I)$, the normal levels by m,I-i-t, and the updated levels by m,I-T-t+1. The random displacement's scale variable.

$$M(I) = srate * Rand(0,1) + M(Ind_{BEST}) \quad (4)$$

$$M(S) = lrate * rand(0,1) + M(Ind_{BEST}) \quad (5)$$

During the exploration phase, either one made with the presumption that the infected person can be introduced up to a certain distance or moved inside a limited area that doesn't go beyond the $s\boldsymbol{U}ate$. This is categorised as short distance development for $srate$. Beyond the typical ambient level, contaminated personal modifications have the potential to significantly start the investigation process. Many people are considered to be at risk of contracting the illness. Using the previously given parameters, a neighbourhood > = 0.5 can be noticed by the use of local variables such as $l\boldsymbol{U}axe$ and $s\boldsymbol{U}ate$. Moving into a neighbourhood exposes a person to the highest concentration of pollutants in that particular area, which heals the illness [19].

Introduction to insecure people

Since the basement lacks base areas, a random numerical dispersion can be used to build the base population there. The equation allows for the generation of populations. N, 2, 3, and N can also be used to define me.

$$Individual_i = L_i + rand(0,1) * (U_i + L_i) \quad (6)$$

The set of polluted individuals in the T era can be used to calculate the current ideal's result, which is presented as follows.:

$$BEST\ S = \begin{cases} GbEST, fitness(CBEST < Fitness\ (GBEST) \\ CBEST, fitness\ (CBEST \geq (GBEST) \end{cases} \quad (7)$$

The target ability in this instance may be categorised as the best arrangement in the T. health era; globally and currently, the best arrangement is described as $CBEST$, $HB\mathbf{G}T\ S$. Since COVID-19 and its related viruses are both super-spreaders and Ebola transmitters, this review categorises them as pollutants.

Using different calculations, this scenario predicts that S, I, H, R, V, D, and Q will advance at a rate commensurate with the amount of time. The schedule for this evaluation is as follows:

$$\frac{\partial s(T)}{\partial T} = \pi - \big(\beta_1 i + \beta_3 d + \beta_4 r + \beta_2 (re)\big)s - (\tau s + \Gamma 1) \quad (8)$$

$$\frac{\partial i(T)}{\partial T} = (\beta_1 i + \beta_3 d + \beta_4 r + \beta_2 (re)\lambda)S - (-(\Gamma + \gamma)i - \tau s) \tag{9}$$

$$\frac{\partial h(T)}{\partial T} = \alpha I - (\gamma + \varpi)h) \tag{10}$$

$$\frac{\partial r(T)}{\partial T} = \gamma i - \Gamma R \tag{11}$$

$$\frac{\partial v(T)}{\partial T} = \gamma i - (\mu + \nu)V \tag{12}$$

The specifications given before, which are a float-category number with a limit, are regarded as measurement jobs. It is selected from the overall criterion difference conditions that are produced by a dramatic currency type or measurement difference conditions, regardless of the related F capabilities. Here, the percentage of the local vulnerable population that gets activated varies in pace. The power vector current scale is then used to determine the total number of insecure individuals in the D period. can provide an analogous cycle for calculating an individual's time. I use many ratios in the Q, D, V, R, and H vectors. Speech acknowledgment, as well as their preferred manner and cognitive process, are considered. The RNN's weight parameter can be found using the EOA method. A thorough flowchart of the suggested procedure is displayed in Figure 4.

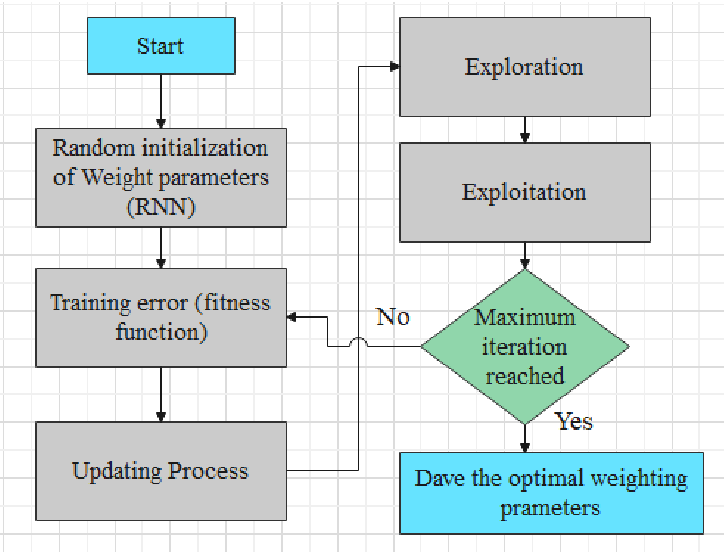

Fig 4: Flowchart of the projected technique

The initial weight parameters of the EOA are set in an arbitrary way. Next, the RNN's weight parameters are chosen depending on the training error. After saving the data, we use the fitness function to determine the weight parameters (training error). The EOA updating process is used to choose the RNN's efficient weight parameter. Finally, the industry assesses fire risk using the recommended controller (oil and gas industry). At last, the optimized risk indexing is proceeding. In this research, different variables are considered which are related to fire occurrence. Few variables such as distance from the fire brigade, size, floors, years can be created objectively but many other variables are related to subjectively. Use the Korean fire occurrence statistics to verify the fire danger for each industry. Numerous factors that are connected to the occurrence of fires are contained in this database. There are two methods for assessing risk in this study. In the beginning, EDLM is used to make the event happen. Additionally, risk index fire occurrence, the parameters-based index is considered. Here, the prediction accuracy and life parameter are a performance metrices for risk assessment prediction and fire risk indexing.

4. Performance Evaluation

This section presents the anticipated technique's performance evaluation. The planned method is assessed concurrently with the execution procedure. The proposed method is built using MATLAB programming R2016b, 6GB RAM, and an Intel Core i5-2450M CPU running at 2.50GHz, together with PC behaviours, to validate it. To bolster the efficacy of the recommended approach, information is obtained from the reference [20]. The anticipated technique was validated using real-time data from the industries affected by the Korea fire. The simulation parameters for this fire risk assessment are listed in Table 1. Performance indicators like as recall, precision, specificity, accuracy, sensitivity, and F Measure are used to assess the effectiveness of the proposed technique. It is compared with traditional techniques like SVM, RNN, and ANN, respectively, to validate the results.

Table 1: Simulation Variables

S. No	Technique	Description	Value
1	Proposed Method	Iteration	100.0
2		Lower bound	-5.12
3		Number of Decision Variables	5.0
4		Number of Populations	50.0
5		upper limit	5.120

Dataset Description:

A total of 201082 data points is included in this database, which takes into account 107 parameters that both cause and prevent industry fires. These criteria include the KFRI 6 percent rank, KFRI 5 percent rank, KFRI 4 percent rank, and KFRI 1 percent rank. They also contain the construction year, kind of construction, KFRI, KFRI 4, KFRI 3, and KFRI 2 percent ranks, and the distance between buildings. additional insurance savings There are three different fire departments: Public Fire Service 2, Public Fire Service 3, Public Fire Service 4, First Public Fire Service Emergency alarm systems 1, Fire detection systems 2, The ratio that is protected by the fire detection system, Auxiliary equipment required for fire departments 1, Evacuation systems 2, Evacuation systems 1, Fire compartment 2, Fire compartment 1, Emergency notifying systems 2, Emergency alarm systems 2, The sprinkler system, the total flooding gas system 1, the fire detection system, and the total flooding gas system 2 Fire extinguisher 2, standpipe 1, sprinkler 1, hydrant 2, Safety management 1, fire extinguisher 1, static electricity, high voltage, high temperature, high pressure, and all of the aforementioned flammable gases hazardous materials, intense labour, electricity-related facility, First Basic Process 2. Facilities for gas, fire, and hazardous materials, fire burden, Two occupant movements, two rooms, one accommodation, two multiple uses, and one multiple use The size, construction, average level of damage, inspection time, and inspection year of the building the fire's spread, Average number of casualties, total area damaged, and so on.

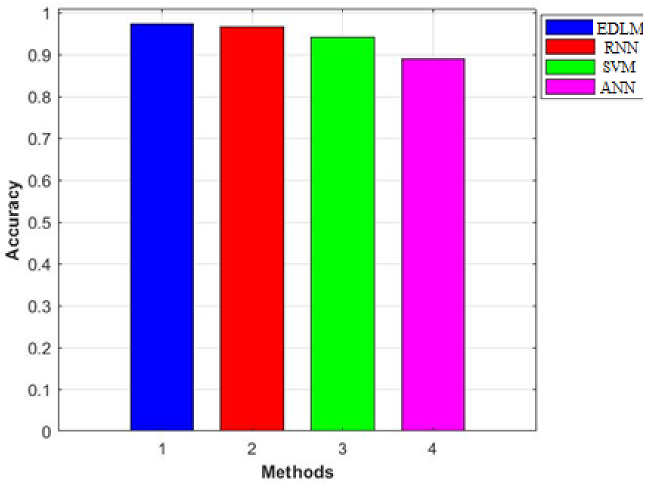

Fig 5: Accuracy

The predicted technique, depicted in Figure 5, is validated by the accuracy measure. To support its application, the proposed technique is described and compared with conventional techniques such as RNN, SVM, and ANN. The anticipated methodology has been accomplished; the accuracy measure is 0.98. Furthermore, RNN has been accomplished with an accuracy measure of 0.93. With the achievement of SVM, the accuracy measure is 0.90. The accuracy measure of the achieved ANN is 0.87. According to the validation, the planned technique produces accurate and efficient results for assessing fire risk in the industrial setting. The anticipated technique, depicted in Figure 6, is validated by the precision measure. To support its application, the proposed technique is described and compared with conventional techniques such as RNN, SVM, and ANN. The anticipated method has been completed; the precision value is 0.92. Furthermore, RNN has been accomplished with a precision measure of 0.91. SVM has been accomplished, with a precision score of 0.89. An ANN with a precision measure of 0.85 has been achieved. According to the validation, the planned technique produces accurate and efficient results in terms of measuring fire risk in the industrial setting.

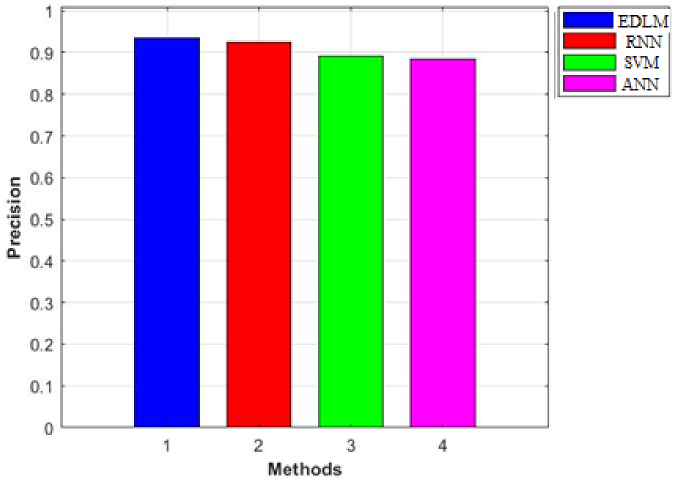

Fig 6: Precision

Figure 6 presents the predicted technique, which is validated by the recall measure. To support its application, the proposed technique is described and compared with conventional techniques such as RNN, SVM, and ANN. The planned approach has been used; the recall percentage is 0.93. Furthermore, RNN has been accomplished with an accuracy measure of 0.91. SVM has been accomplished; the recall measure is 0.90. The achieved ANN has a recall measure of 0.87. According to the validation, the anticipated technique produced effective results in the recall measure for the industry's fire risk assessment. In order to validate the predicted technique shown in Figure 7, the sensitivity measure is taken into consideration. To support its application, the proposed technique is described and compared with conventional techniques such as RNN, SVM, and ANN. The anticipated method has been accomplished; the sensitivity value is 0.93. Furthermore, RNN has been accomplished with a sensitivity measure of 0.92. The resulting SVM has a sensitivity measure of 0.87. The achieved ANN has a sensitivity measure of 0.85. According to the validation, the planned technique produces effective results in the sensitivity measure for assessing fire risk in the industrial setting.

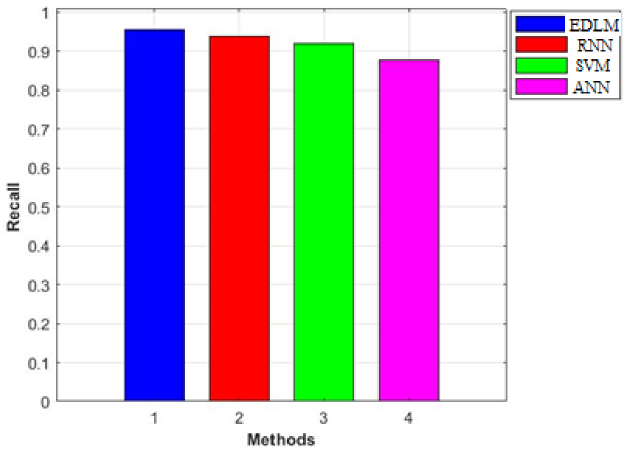

Fig 7: Recall

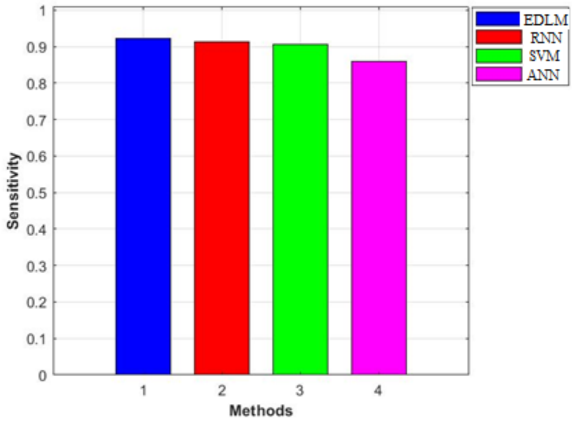

Fig 8: Sensitivity

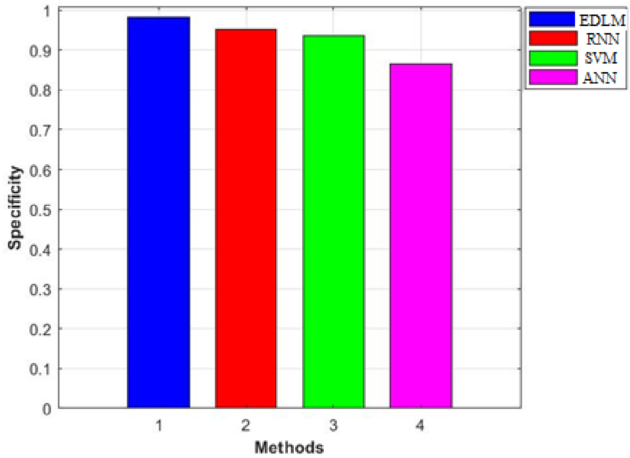

Fig 9: Specificity

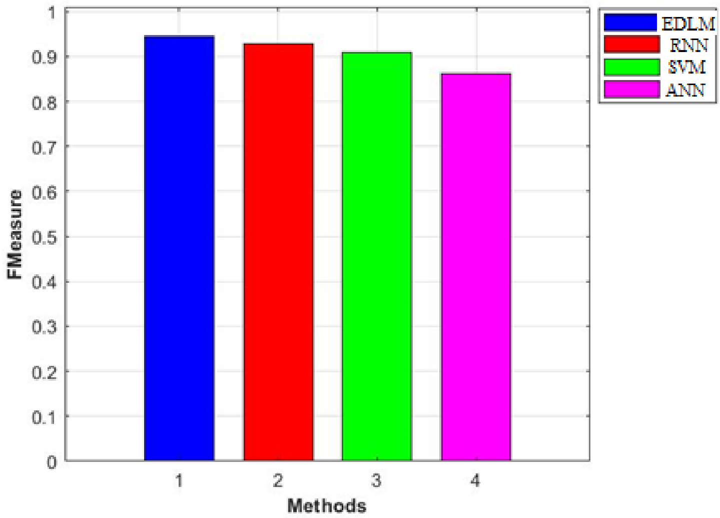

Fig 10: F Measure

The specificity measure validates the expected technique, which is shown in Figure 8. To support its application, the proposed technique is described and compared with conventional techniques such as RNN, SVM, and ANN. The anticipated method has been completed; the specificity value is 0.94. Furthermore, RNN has been accomplished with a specificity score of 0.94. The acquired specificity measure for SVM is 0.89. After ANN development, the specificity measure is 0.85. According to the validation, the planned technique produced effective results in terms of the industry's measure of specificity for fire risk assessment. The projected technique shown in figure 9 and 10 is validated using the F Measure measure. To support its application, the proposed technique is described and compared with conventional techniques such as RNN, SVM, and ANN. The anticipated method has been completed; the F Measure measure is 0.94. Furthermore, RNN has been accomplished; the F Measure measure is 0.93. After achieving SVM, the F Measure metric is 0.88. The achieved measure of F Measure for ANN is 0.87. According to the validation, the planned technique produced effective results in the F Measure for assessing fire risk in the industrial setting.

5. Conclusion

This study presents the development of EDLM for optimum risk indexing and fire risk assessment. DRNN and EOA are combined to create the proposed EDLM. With the help of EOA, the DRNN's weight update procedure is accomplished. At first, real-time data is gathered from Korean fire incidents. Under typical conditions, the current fire prediction models do not offer appropriate levels of accuracy. Under typical conditions, the current fire prediction models do not offer appropriate levels of accuracy. The fact that there are many different elements influencing fire occurrence and that fires occur rarely serves as validation for this result. In order to improve fire occurrence accuracy, an effective deep learning model is presented. Furthermore, the fire prediction model serves as the foundation for the development of the fire risk indexing model. The proposed method is put into practise and contrasted with more traditional methods like RNN, SVM, and ANN, in that order. Based on the analysis, the anticipated method produces effective results in terms of performance metrics. Applications for fire risk assessment will take into account the particular data related to the oil and gas sector in the future.

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