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Use of Machine Learning to Detect Dangerous Level of Coal Mine Methane (CMM) Concentrations During Underground Mining Operations

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Abstract

Underground coal mining is considered to be a highly dangerous activity and has been responsible for large amounts of accidents causing the death of many mine workers. One of the factors responsible for the fatal aspect of underground coal mining is the presence and accumulation of toxic gases during underground mining operations. This paper focused its investigation specifically on coal mine methane (CMM) which is released as a result of the extraction of coal and the disturbance inflicted to surrounding rocks' formation during deep mining operations. Methane is considered a highly dangerous gas as it holds the capacity to cause explosions due to its high inflammable nature. It also can displace oxygen which eventually leads to asphyxiation. This research was based on the use of machine learning models to successfully predict dangerous concentrations of methane over the authorized threshold. Those predictions were made from a dataset containing information on the temperature, airflow, humidity, pressure and methane concentration at an underground coal mine. The temperature, airflow, humidity and pressure measurements were recorded by a series of sensors namely anemometers and component sensors THP2/93. Three machine learning classification models were implemented and compared with the objective towards finding the best model to predict and detect dangerous level of coal mine methane. The models that were investigated include: Naïve-Bayes, logistic regression and artificial neural networks (ANN). The paper concluded with an engineering decision matrix that illustrated the precision of these models towards predicting and detecting dangerous level of methane concentration in underground mines. Furthermore, recommendations for capacity improvement towards successfully predicting and detecting dangerous level of coal mine methane from an artificial intelligence's perspective were provided.

Keywords: coal mine methane (CMM); machine learning; artificial intelligence; sensors

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1. Introduction

There are three types of mining operations to extract ores. These types of operations are notably open surface mining, deep mining and sea water mining. As for deep mining or also known as underground mining operations, the most common technique used is longwall mining because it is considered as the safest and most productive technique [1]. However, past research clearly demonstrates that this specific technique of extraction releases high and dangerous concentrations of methane, also referred as coal mine methane (CMM), in the surrounding underground environment [2]. CMM owing to its inflammable nature, has been responsible for a large number of lethal explosions around the world. A document signed by the United Nations detailed those fatal accidents as followed: 214 deaths on the 14 February 2005 in the Sunjlawan mine of China, 108 deaths on the 19 March 2007 in Ulyanovskaya mine of Russia, 80 deaths on the 19 November 2007 in Zasyadko mine of Ukraine, 43 deaths on the 20 September 2006 in Lenina mine of Kazakhstan, 29 fatalities in Upper Big Branch, West Virginia, United states of America on the 5 April 2010 and 12 deaths also in West Virginia, most precisely in Sago on the 14 February 2005 [3]. As result, CMM's explosions are considered amongst the most lethal accidents when it comes to underground or deep mining operations, hindering the safety and productivity of the mining's environment as well as its industry. One way to ensure that the concentration of coal mine methane does not exceed the safe and permissible threshold is the use of ventilation. According to a study performed on the safety of longwall mining, researchers supported the use of ventilation as the most effective methods for the control of gases with a special focus of coal mine methane, known to be present and released in large volumes during longwall mining's activities [4].

To achieve optimal ventilation in underground mining regions, it is important to localize the regions that present high concentrations of CMM. This is achieved by the implementation of a sensing and metrification strategy. Since the concentration of CMM is largely attributed to its capacity of accumulation and dispersion which itself is dependent on physical parameters like temperature, humidity, pressure and airflow, sensors are placed in various locations of underground mines to collect data which contributes to better management of CMM through optimal ventilation usage. The type of sensors commonly used are normally threshold triggering and continuous monitoring. Threshold triggering sensors normally emit an output whenever the measured parameter exceeds the permissible threshold. On the other side, continuous monitoring sensors collect real-time data over a period of time. The use of triggering sensors in the management of CMM in underground mining conditions comes with its own set of challenges and disadvantages that compromise the safety of the mines as well as its productivity. Triggering sensors emit an alarm only when the maximum permissible CMM threshold has been exceeded. This type of system only allows for reactive measures which leave little to no time to respond efficiently to a hazardous situation. This can lead to a fatal occurrence in case of late activations of the sensors. Past studies demonstrate that under deep mining conditions, the response time of a sensor varies between 210 and 257s while the recovery time sits between 142 to 241 s [5]. These data clearly show that it takes too much time for a triggering sensor to pick up high concentrations of CMM, hence increasing the risk of explosions in underground mines. A study focused on the influence of environmental factors like humidity alongside pressure, concluded that those natural factors interfere with the capacity of these sensors by introducing an element of delay leading to late alarms [6]. As a result, the reactive cognition aspect of the methane management system is heavily compromised and highly hazardous and dangerous situations are not dealt appropriately, leading to explosions. To improve the detection of CMM, artificial intelligence models are employed to predict dangerous concentrations of CMM with a high level of precision and accuracy. This improves the cognition attribute of underground CMM management by replacing reactive decisions with proactive ones. Tutak, Krenicky, Pirnik, Brodny and Grebski proposed a Multi-Layer Perceptron Neural Network for predictions of CMM in underground coal mining [7]. This research was focused on longwall mining and concluded that it was possible to generate forecasts of CMM with a high level of accuracy.

According this paper, predictions made within a forecast window ranging from 5 to 60 min were considered as acceptable. A different study performed in China, most precisely at the Buertai Coal Mine, proposed a prediction model for methane concentration, namely an Improved Black Kite Algorithm (BKA) working together with an Informer Bidirectional Long Short Term Memory algorithm [8]. This proposed algorithm made use of several features which includes historical data on methane concentrations, temperature as well as wind speed and results obtained indicated a high predictive accuracy of the model in terms of convergence and speed as well as an elevated degree of robustness. Nie et al. [9] studied the characteristics of the surrounding mining environment with the objective of better understanding the manner in which CMM spreads in underground mines. This allowed the researchers to present a methane prediction model based on the Gaussian plume model, genetic algorithms and BP neural networks (Back Propagation Neural Network). This model presented a high level of accuracy in monitoring the level of CMM and is considered reliable due to its ability to continuously train on daily real-time data. Another machine learning technique that was used successfully in methane prediction is the support vector machine algorithm [10]. This research focused on building a multi-sensor prediction model for methane predictions by combining methodologies from information fusion alongside support vector machines. To achieve a high predictive accuracy of coal mine methane, it is common and highly advisable to use a palette of features as demonstrated by Zhiqiang Luo et al. [11] in building their eXtreme Gradient Boosting algorithm (XG Boost). For this model, the researchers chose to make sure of natural parameters like temperature and past historical data of methane concentrations to train and test their machine learning models. Results obtained indicated that the tested models had faster training speeds compared to existing ones and a lower percentage of prediction errors.

From the above, it is clear that a robust artificial intelligent mode with a high degree of accuracy can successfully predict dangerous concentrations of methane, enhancing the safety of underground mining operations. This paper analyzed the computational ability and reliability of three machine learning classification models that successfully predict and classify dangerous concentrations of coal mine methane in underground mines. Those three machine learning classification models are the Naïve-Bayes, Logistic Regression and Artificial Neural Network. The aim of this paper is to perform a comparative analysis of these three algorithms in regards to their capacity of predicting dangerous level of concentrations of CMM with a high degree of accuracy. This paper, with the results obtained, will lay the foundation to build improved machine learning algorithms with higher degree of accuracy in regards to the prediction of dangerous concentrations of CMM.

2. Research Methodology

The research methodology is divided into two parts: the first part being preparing the sensing dataset in order to be used as input for the classification models and the second part being the design and implementation of the three above discussed machine learning classification models.

2.1. Description of the Sensing Data and Machine Learning Algorithms

This study investigated and compared the use of three machine learning classification models, namely Naïve Bayes, Logistic Regression and Artificial Neural Network to predict and classify efficiently concentrations of methane into safe and unsafe categories. These predictions were made based on data from sensing data which are past historical concentrations of methane, temperature, humidity, airflow and pressure. These data were obtained from 28 different sensors placed at different locations in the underground mine [12]. The underground mine that was used for this study is located in the Upper Silesian coal basin, in the region of Voivodeship in Poland. The data was recorded every 1 s and two groups of data were recorded with the first one focusing on climatic parameters like temperature and the second group focusing on the activities focusing on the cutter loader operation. For the purpose of this research paper, only the climatic conditions that are temperature, pressure, humidity and airflow were considered as input to the different machine learning models. This is in line with the philosophy of the research to test the predictability of those machine learning models from a pure climatic and environmental perspective before introducing other input that relate to the human's activities performed in mines. The following section depicts the data handling procedure of this research as follows:

1. Cleaning the dataset to ensure that there are no missing values and remove any duplicated readings.
2. Select the required features that will serve as input to the machine learning classification models. Those features are pressure, temperature, humidity and airflow.
3. Select the required methane meters and associated historical data as output.
4. Based on a chosen threshold (e.g., 1.0), classify methane's concentration as safe and unsafe.
5. Perform checks on different portion of dataset to check number of safe and unsafe cases in each data clusters.
6. Use the data as input to three different machine learning classification models. Those models are the Naïve-Bayes, Logistic Regression and Artificial Neural Networks.
7. Print out the classification report to display the values for the following statistical parameters:

The following section addresses the development of the three machine learning classification algorithms that are deployed for this research.

2.1.1. Naïve-Bayes Machine Learning Classification Model

The Naïve-Bayes Classification Model is used as a first baseline model for the purpose of this research and is based on the assumption of attribute independence. This means that all the features or attributes are not related to each other. Naïve Bayes is built from the Bayes Theorem as shown below:

$$P(C|X) = \frac{P(X|C) \times P(C)}{P(X)}$$

The Bayes theorem above consists of two parameters which are C and X. C represents the class that needs to be predicted while X represents the different features that are used as inputs. The P(C|X) indicates the probability of happening of event C given X has happened. In order to form the Naïve Bayes equation, it is assumed that each features of x are independent of each other, giving the following equation:

$$P(x_1, x_2, ..., x_n|C) = \prod_{i=1}^{n} P(x_i|C)$$

For the purpose of this study, the x parameter will relate to the climatic conditions of the underground mine which are temperature, pressure, airflow and humidity. The C will relate to the different categories of CMM's concentrations in underground mines. Two categories will be used for this paper and they are Safe and Unsafe. The purpose of the Naïve-Bayes classification algorithm will be to use the different input parameters such as temperature, pressure, humidity alongside airflow to predict and classify CMM's concentrations as safe or unsafe.

Figure 1 illustrates the algorithm that was built to implement the Naïve-Bayes algorithm in predicting and classifying the concentrations of CMM as safe or unsafe during underground mining operations.

```
import os
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import classification_report, accuracy_score
os.chdir('C:/MEng Research/methane_data')
print(os.getcwd())
files = os.listdir()
print(files)
size = 2000000
TwoMillionRecords = pd.read_csv("methane_data.csv", nrows=size)
print(TwoMillionRecords.head())
print(f'The file contains {TwoMillionRecords.shape[0]} rows.')
columns_to_keep =
['second','TP1711','MM263','MM264','MM256','RH1712','BA1713','TC862','AN422']
New = TwoMillionRecords[columns_to_keep]
New.to_csv('Methane_SeventhTestingFileNaiveBayes.csv', index=False)
MethaneSeventhTest = pd.read_csv('Methane_SeventhTestingFileNaiveBayes.csv')

#We rely on the principle of proximity and calculate an average
MethaneSeventhTest['average_methane'] =
MethaneSeventhTest[['MM263','MM264','MM256']].mean(axis=1)
MethaneSeventhTest['condition']=MethaneSeventhTest['average_methane'].apply(l
ambda x:'UnSafe' if x>1 else 'Safe')
print(MethaneSeventhTest.head())
MethaneSeventhTest.to_csv('Methane_FinalSeventhTestingFileNaiveBayes.csv',
index=False)

#Build the Naive-Bayes Model now
X = MethaneSeventhTest[['TP1711','AN422','MM263','MM264','MM256']]
Y = MethaneSeventhTest['condition']
X_train,X_test,Y_train,Y_test =
train_test_split(X,Y,test_size=0.01,random_state=9)
NaiveBayesModel = GaussianNB()
NaiveBayesModel.fit(X_train,Y_train)
Y_Predict = NaiveBayesModel.predict(X_test)
print("Accuracy:", accuracy_score(Y_test, Y_Predict))
print("\nClassification Report:\n", classification_report(Y_test, Y_Predict))
```

Figure 1. Naïve-Bayes Classification Algorithm.

2.1.2. Logistic Regression Machine Learning Classification Model

The second model that was implemented is known as the Logistic Regression Classification Model. This model is by nature a statistical classification model which outputs a probability that sits between zero and one. Compared to the Naïve-Bayes, this model does not require the assumption of independence between the input features hence making it a more robust alternative compared to the previous model.

Figure 2 illustrates the algorithm that was built to implement the Logistic Regression algorithm in predicting and classifying the concentrations of CMM as safe or unsafe during underground mining operations.

```
import os
import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score,
confusion_matrix
from sklearn.model_selection import train_test_split

os.chdir('C:/MEng Research/methane_data')
print(os.getcwd())
files = os.listdir()
print(files)
MethaneTest = pd.read_csv('Methane_FinalSeventhTestingFileNaiveBayes.csv')
print(MethaneTest.head())
print("Number of rows:", MethaneTest.shape[0])

#Build the Logistic Regression Model now.
X = MethaneTest[['TP1711','AN422','MM263','MM264','MM256']]
Y = MethaneTest['condition']
X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.3,stratify =
Y,random_state=22)
Log_Reg =
LogisticRegression(class_weight='balanced',max_iter=100000,solver='liblinear'
)
Log_Reg.fit(X_train,Y_train)
print(f"Number of iterations used: {Log_Reg.n_iter_}")

#Predicting the accuracy and classification report
Y_Prediction = Log_Reg.predict(X_test)

print("Accuracy:", accuracy_score(Y_test, Y_Prediction))
print("\nClassification Report:\n", classification_report(Y_test,
Y_Prediction))
print("\nConfusion Report:\n",confusion_matrix(Y_test, Y_Prediction))
```

Figure 2. Logistic Regression Classification Model.

2.1.3. Artificial Neural Network (ANN) Classification Model

The third model that was implemented is known as the Artificial Neural Network (ANN) Classification Model. The latter was chosen as it has the inherent capacity to learn and simulate models where relationships between input's structures are by nature non-linear, hence raising the level of complexity of predictions and by default, being a better alternative than the logistic regression model. It is also an upgrade over the Naïve-Bayes as it does not assume independence of features.

Figures 3 and 4 illustrate the algorithm that was built to implement the Artificial Neural Network algorithm in predicting and classifying the concentrations of CMM as safe or unsafe during underground mining operations.

```
First_subset = desired_file[columns_to_keep]
number_of_rows = len(First_subset)
print(First_subset['condition'].value_counts())
X= First_subset[['second','TP1711','MM263','MM264','MM256']]
print(X.head())
Y = First_subset[['condition']]
print(Y.head())
X_train,X_test,Y_train,Y_test=
train_test_split(X,Y,test_size=0.3,random_state=9)
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
Y_train = Y_train['condition'].map({'Safe':0,'UnSafe':1})
Y_test = Y_test['condition'].map({'Safe':0,'UnSafe':1})
#Convert test features to numpy float32
Y_train = np.array(Y_train,dtype = np.float32)
Y_test = np.array(Y_test,dtype = np.float32)

X_train = np.array(X_train,dtype=np.float32)
X_test = np.array(X_test,dtype=np.float32)

#Build the ANN Model
model = Sequential()
model.add(Dense(units=32,activation='relu',input_shape=(5,)))#Hidden layer
model.add(Dense(units=1,activation='sigmoid'))

#Compile
opt = Adam(learning_rate=0.00009)
model.compile(optimizer=opt,loss='binary_crossentropy',metrics=['accuracy']
)

#We implement the early stopping
early_stopping = callbacks.EarlyStopping(
    min_delta=0.0001,
    patience=20,
```

Figure 3. Artificial Neural Network Algorithm (Part 1 of 2).

```
    restore_best_weights=True,
)
#Training the Artificial Neural Network
history = model.fit(
    X_train,
    Y_train,
    batch_size=32,
    epochs =150,
    callbacks=[early_stopping],
    validation_split=0.3
)
#Prediction part
Y_Prediction = model.predict(X_test)
Y_Prediction = (Y_Prediction>0.5)

#Print confusion matrix and classification report
cf_matrix = confusion_matrix(Y_test,Y_Prediction)

#Print Classification Report
print(classification_report(Y_test,Y_Prediction))
```

Figure 3. Artificial Neural Network Algorithm (Part 2 of 2).

3. Results and Discussions

This section summarizes the results obtained after deploying the three classification machine learning models (Naïve Bayes, Logistic Regression and Artificial Neural Network).

The Naïve Bayes Model was deployed and simulations were performed on the dataset consisting of 9,197,561 safe events indicating a safe level of CMM's concentration and 2369 unsafe events indicating a dangerous level of CMM's concentration. Simulations were performed on different sample sizes in the following combinations: 1,000,000, 2,000,000, 3,000,000, 4,000,000, 5,000,000, 6,000,000, 7,000,000, 8,000,000 and 9,199,930. The detailed results for those simulations is illustrated as shown below in both Figures 4 and 5 respectively:

Total Number of Simulations	Number of Safe Cases	Precision	Recall	f1-score
1000000	999812	1	1	1
2000000	1999798	1	1	1
3000000	2999526	1	1	1
4000000	3998436	1	1	1
5000000	4997965	1	1	1
6000000	5997935	1	1	1
7000000	6997935	1	1	1
8000000	7997817	1	1	1
9199930	9197561	1	1	1

Figure 4. Simulation Results for Safe Cases using Naïve Bayes.

Total Number of Simulations	Number of Unsafe Cases	Precision	Recall	f1-score
1000000	188	0.25	1	0.4
2000000	202	0.32	1	0.48
3000000	474	0.29	1	0.45
4000000	1564	0.34	1	0.51
5000000	2035	0.31	1	0.48
6000000	2065	0.25	1	0.35
7000000	2065	0.17	1	0.29
8000000	2183	0.18	1	0.31
9199930	2369	0.18	1	0.3

Figure 5. Simulation Results for Unsafe Cases using Naïve Bayes.

In the second part of this section, the Logistic Regression Model was deployed and simulations were performed on the dataset consisting of 9,197,561 safe events indicating a safe level of CMM's concentration and 2369 unsafe events indicating a dangerous level of CMM's concentration. Simulations were performed on different sample sizes in the following combinations: 1,000,000, 2,000,000, 3,000,000, 4,000,000, 5,000,000, 6,000,000, 7,000,000, 8,000,000 and 9,199,930. The detailed results for those simulations is illustrated as shown below in Figures 6 and 7 respectively:

Total Number of Simulations	Number of Safe Cases	Precision	Recall	f1-score
1000000	999812	1	1	1
2000000	1999798	1	1	1
3000000	2999526	1	1	1
4000000	3998436	1	1	1
5000000	4997965	1	1	1
6000000	5997935	1	1	1
7000000	6997935	1	1	1
8000000	7997817	1	1	1
9199930	9197561	1	1	1

Figure 6. Simulation Results for Safe Cases using Logistic Regression.

Total Number of Simulations	Number of Unsafe Cases	Precision	Recall	f1-score
1000000	188	0.48	1	0.65
2000000	202	0.43	1	0.6
3000000	474	0.45	1	0.62
4000000	1564	0.47	1	0.64
5000000	2035	0.53	1	0.7
6000000	2065	0.51	1	0.68
7000000	2065	0.5	1	0.67
8000000	2183	0.45	1	0.62
9199930	2369	0.43	1	0.6

Figure 7. Simulation Results for Unsafe Cases using Logistic Regression.

In the third part of this section, the Artificial Neural Network Model was deployed and simulations were performed on the dataset consisting of 9,197,561 safe events indicating a safe level of CMM's concentration and 2369 unsafe events indicating a dangerous level of CMM's concentration. Simulations were performed on different sample sizes in the following combinations: 1,000,000, 2,000,000, 3,000,000, 4,000,000, 5,000,000, 6,000,000, 7,000,000, 8,000,000 and 9,199,930. The detailed results for those simulations is illustrated as shown below:

Total Number of Simulations	Number of Safe Cases	Precision	Recall	f1-score
1000000	999812	1	1	1
2000000	1999798	1	1	1
3000000	2999526	1	1	1
4000000	3998436	1	1	1
5000000	4997965	1	1	1
6000000	5997935	1	1	1
7000000	6997935	1	1	1
8000000	7997817	1	1	1
9199930	9197561	1	1	1

Figure 8. Simulation Results for Unsafe Cases using Artificial Neural Network.

Total Number of Simulations	Number of Unsafe Cases	Precision	Recall	f1-score
1000000	188	0.98	1	1
2000000	202	1	0.74	0.85
3000000	474	1	0.7	0.83
4000000	1564	0.98	0.83	0.9
5000000	2035	0.98	0.85	0.91
6000000	2065	0.98	0.88	0.92
7000000	2065	1	0.75	0.86
8000000	2183	0.98	0.93	0.96
9199930	2369	0.99	0.83	0.9

Figure 9. Simulation Results for Unsafe Cases using Artificial Neural Network.

Based on the results above, it is clear that all the three models perform really well in predicting the safe events but does that mean that they are all robust and efficient enough in detecting and predicting dangerous concentrations of methane? The answer to this question is no. There is a major imbalance in the dataset as shown in the figure above. If we consider the dataset in its totality, there are 2369 cases of Unsafe cases over a total of 9,199,930 cases and that amounts to only 0.026%. As a result, if one takes the accuracy of these models as a metric to measure their strength, it will lead to an erroneous conclusion as the accuracy tell us how well the model is doing and in this case that will relate to how good is the model at picking up safe cases. The minority class of unsafe classes will be therefore overlooked in such an analysis and that will not contribute in creating an algorithm that is good in detecting unsafe concentrations of methane. Therefore, other metrics need to be employed to correctly assess the robustness and efficiency of the above tested models in terms of their predictability capacity. The metric that has been considered is the precision. The precision parameter contributed in answering the following question: Out of all the unsafe events detected, how many are really unsafe events? Basically it ensures that only the real cases of unsafe events are picked up and all the false alarms are filtered out.

Figure 5 clearly shows that for the simulation of the Naïve-Bayes Algorithms, a low precision was achieved across the different sample sizes. This indicates that the model performed poorly in detecting the real cases of unsafe events and this generated a lot of false alarms. This is an example of an algorithm that cannot be applied in a real life situation because it will wrongly flag standard cases as unsafe ones causing unnecessary disruptions during underground mining operations. Figure 7 shows an improvement in the predictive capacity of the model when a logistic regression algorithm is used. The precision presents a maximum value of 0.53 and a minimum value of 0.43. Despite this improvement, the logistic regression algorithm still performs poorly as those values indicate that around half of the predictions made are actually made up of false positives. However, Figure 9 shows a drastic improvement in the predictive capacity of detecting dangerous concentrations of methane when an artificial neural network is deployed. The minimum value recorded is 0.98 and a maximum value of 1.0 was recorded in three different simulations over three different datasets. That indicates that in three different instances, the algorithm correctly identified all the different unsafe cases of methane without any false positives. In order to improve those predictions, it must be noted that since the dataset is very imbalanced in nature, it is therefore highly recommended that resampling methods like SMOTE must be applied in order to improve the machine intelligence algorithms in their learning capacity towards the minority class, precisely the Unsafe class for this specific research.

4. Conclusions

This research presented an approach into comparing three machine learning models with the objective down the line to build a classification model that has a high predictability ability to detect dangerous or unsafe concentrations of methane. The research started with handling a dataset containing records of methane concentrations, environmental or climatic factors as well as physical factors. Since there was a desire to build predictive models that are climatic or environmentally oriented for the prediction of coal mine methane, the assumption was made that the only inputs to the machine learning model that will be considered are the temperature, airflow, pressure as well as the humidity. The dataset was cleaned and the required content was extracted to serve as input to the different machine learning models. The three models were tested on different sample sizes of data and a classification report was issued after each simulation with the necessary statistical parameters to evaluate the robustness and reliability of these models. The parameters that were used were the precision, f1 score and the recall. These parameters were selected as they can provide a robust answer to the question "How efficient are the models in picking the unsafe situations keeping in mind that there is a major imbalance favoring the safe class over the unsafe ones? The evidence displayed in Section 4 indicated that the Artificial Neural Network (ANN) performed better compared to the Naïve Bayes and the Logistic Regression in when it came to the prediction of unsafe cases. This research indicates that machine learning models built on neural networks algorithms perform better in their predictive capability in this type of situations. A further study into this research will include the use of more advanced deep learning models working in a hybrid approach with optimization algorithms like the Black Kite Algorithm (BKA).

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