

MONITORING AND ALERTING OF HAZARDOUS GASES IN MUNICIPAL SOLID WASTE USING MACHINE LEARNING TECHNIQUE

Er.S.Murugeswari

Dept. of Computer Science
VPMM College of Engineering and Technology,
Krishnankovil, Virudhunagar., India
eshwari.31.8.85@gmail.com

Mr.R.Rajkumar.,M.E,MISTE

Associate Professor: dept. of Computer Science
VPMM College of Engineering and Technology,
Krishnankovil, Virudhunagar., India
hr.rajkumar11@gmail.com

Abstract-In recent times, the rate of urbanization is proliferating; thus, there is a need to find a sustainable way for an urban development plan. There is rapid growth in the concept of smart cities all around the globe. A smart city is always incomplete without a smart waste monitoring structure that can manage the waste collection of the entire city. This paper proposes a Forest Fire alerting system, which keeps track of the hazardous gases produced by dumped waste by integrating a network of gas sensors. Land fill sites collect tons of municipal solid waste (MSW) using an open dump mechanism, causing gases to emerge, which may cause disease and the greenhouse effect. Mainly, landfill environments are observed using a portable system that does not continuously monitor and measure emitted gas levels. It is also difficult to evaluate changes in landfill emissions over the long term unless they are monitored at regular intervals according to a detailed plan. This paper presents a new monitoring method to measure gas levels in landfill sites, which documents dynamic changes in gas composition concentrations over the long term. The system was placed in the middle area of the landfill and was charged using solar panels for convenience and greater efficiency during monitoring.

I.INTRODUCTION

OVERVIEW OF PROJECT-Fire can make major hazards in this hectic world. All buildings and vehicles used in public transportation have fire prevention and fire protection systems due to the accelerated number in the fire incidents. Also, many of the firms conduct a mock fire drill in every occurrence of months to protect their employees from the fire. This would help them to understand what to do or what not to do when a fire situation happens. Forests are one of the main factors in balancing the ecology. It is very harmful when a fire occurs in a forest. But most of the time, the detection of forest fire happens when it spread over a wide region. Sometimes, it could not be possible to stop the fire. As a result, the damage of the environment is higher than predictable.

OBJECTIVE OF PROJECT-The Main objective of the Gas leakage detection[1] system we propose a novel system for detecting fire using Convolution Neural Networks (CNN). Detection of fire can be extremely difficult using existing Methods of smoke sensors installed in the buildings. They are slow and cost inefficient due to their primitive design and technology. This paper critically analyzes the scope of Artificial intelligence [2] for detection and sending alerts with video from CCTV footages. This project uses self-built dataset containing video frames with fire. The data is then pre-processed [3] and use the CNN to build.

II.LITERATURE SURVEY

1.A. Real- time video fire/smoke detection based on CNN in Anti fire surveillance systems Author: Saponara, S., Elhanashi, A. & Gagliardi. We used a large scale of fire/smoke and negative videos in different environments, both indoor (e.g., a railway carriage, container, bus wagon, or home/office) or outdoor (e.g., storage or parking area). YOLOv2 is a better option compared to the other approaches for real-time fire/smoke detection, working in the visible spectral range. There are not specific requirements for the video camera. Hence, when the proposed solution is applied for safety on-board vehicles, or in transport infrastructures, or smart cities, the camera installed in closed-circuit television surveillance systems can be reused.

2. International Journal of Advance Scientific Research. Forest Fire Detection Using Machine Learning(2020) Author: Pragati, S.S

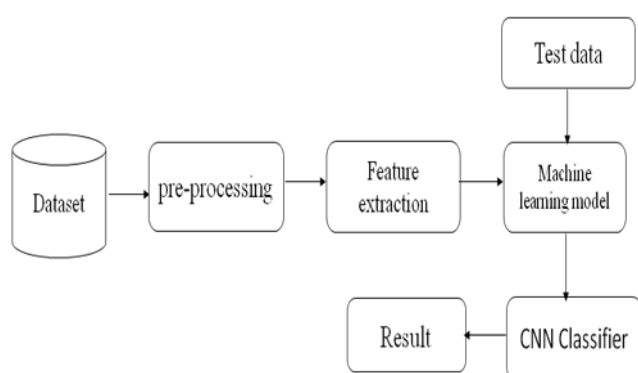
The idea of establishing smart cities in India and globally is tremendously increasing among governmental authorities. There exists several challenges for implementing smart cities, especially in developing countries such as India and China - leading people to a digital world, imparting knowledge to efficiently utilize the smart city resources, accomplishing self-sustainable environment, and so forth. Existing waste collection methods, adopted in cities, are not a viable solution for smart cities. In this paper, we have designed a smart bin solution using IOT [4] Cloud based sensors and actuators. The proposed

approach was designed to create as an end product where the product design was modelled.

3. The authors of (Cheng 2021) developed an approach using a Fast Regional Convolutional Neural Network (Fast R-CNN). A selective search method was used to locate candidate images from the sample images. As proven by the results, fast R-CNN smoke detection showed an increased detection rate and decreased false alarms. Pu and Zhao (Li and Zhao 2020) proposed novel fire detection methods based on advanced object identification CNN models such as Faster-RCNN, R-FCN, YOLO v3 etc. A comparison of proposed and existing fire detection algorithms indicated that those based on object detection, CNNs outperformed other algorithms in terms of accuracy. And, YOLOv3-based model gave an average precision of 83.7%, which is much greater than the precision of the other proposed algorithms.

4. Sousa et al. (2020) summarized recent research attempts to present the common challenges and limitations of these approaches, as well as issues about the dataset quality. Furthermore, they devised a method for transfer learning and utilizing data augmentation techniques that were validated using a tenfold cross-validation scheme. The proposed framework enabled the use of an open-source dataset containing images from over 35 real-world fire events. Unlike video-based works, this dataset contains a high degree of variation between samples, allowing us to test the method in a variety of real-world scenarios. Fernandez et al. (2021) demonstrated a system that can acquire real-time images and process them to perform object detection tasks using RetinaNet and Faster-RCNN. To help contain wildfires, this system is capable of detecting smoke plumes over a large area and communicating with and alerting authorities.

III. PROPOSED METHODOLOGY



Module design and organization

- Analyze the Dataset
- Data Pre-Processing
- Feature Extraction
- Classification

ANALYZE THE DATASET

Data's collection breaks down into two methods. As a side note, many terms, such as techniques, methods, and types, are interchangeable and depending on who uses them. One source may call data collection techniques "methods,[5]" for instance. But whatever labels we use, the general concepts and breakdowns apply across the board whether we're talking about marketing analysis or a scientific research project

DATA PRE-PROCESSING

Organize your selected data [4] by formatting, cleaning and sampling from it.

Three common data pre-processing steps are:

Formatting: The data you have selected may not be in a format that is suitable for you to work with. The data may be in a relational database and you would like it in a flat file, or the data may be in a proprietary file format and you would like it in a relational database or a text file.

Cleaning: Cleaning data is the removal or fixing of missing data. There may be data instances that are incomplete and do not carry the data you believe you need to address the problem. These instances may need to be removed. Additionally, there may be sensitive information in some of the attributes and these attributes may need to be removed from the data entirely.

Sampling: There may be far more selected data available than you need to work with. More data can result in much longer running times for algorithms and larger computational and memory requirements. You can take a smaller representative sample of the selected data that may be much faster for exploring and prototyping solutions before considering the whole dataset.

Machine Learning Data Features:

Categorical features: Features whose explanations or values are taken from a defined set of possible explanations or values. Categorical values can be colors of a house; types of animals; months of the year; True/False; positive, negative, neutral, etc. The set of possible categories that the features can fit into is predetermined.

Numerical features: Features with values that are continuous on a scale, statistical, or integer-related. Numerical values are represented by whole numbers, fractions, or percentages. Numerical features can be house prices, word counts in a document, time it takes to travel somewhere, etc.

FEATURE EXTRATION

Next thing is to do Feature extraction[6] is an attribute reduction process. Unlike feature selection, which ranks the existing attributes according to their predictive significance, feature extraction actually transforms the attributes. The transformed attributes, or features, are linear combinations of the original attributes. Finally, our models are trained using Classifier algorithm. We use classify module on Natural Language Toolkit library on Python. We use the labelled dataset gathered. The rest of our labelled data will be used to evaluate the models. Some machine learning algorithms were used to classify pre-processed data.

The technique of extracting the features is useful when you have a large data set and need to reduce the number of

resources without losing any important or relevant information.

Feature extraction helps to reduce the amount of redundant data from the data set. In the end, the reduction of the data helps to build the model with less machine effort and also increases the speed of learning and generalization steps in the machine learning process.

Practical Uses of Feature Extraction

Auto encoders: The purpose of efficient data coding. Feature extraction is used here to identify key features in the data for coding by learning from the coding of the original data set to derive new one. **Bag-of-Words:** A technique for natural language processing that extracts the words (features) used in a sentence, document, website, etc. and classifies them by frequency of use. This technique can also be applied to image processing.

CLASSIFICATION

Once all the crucial steps are performed including pre-processing, and feature extraction, we move towards classification [7]. There are very many classification techniques proposed by various researchers. All these techniques have several pros and cons. There is a fluctuation in the performance of these techniques as well depending on the data and other prerequisite steps. However, in this research work, classification is performed through CNN [8]. This algorithm is referred to as a supervised machine learning approach that is commonly used for classification and regression problems. CNN is an efficient algorithm that shows encouraging results on a given dataset. The most popular metrics for measuring classification performance include accuracy, precision, confusion matrix, log-loss, and AUC (area under the ROC curve).

1. Accuracy measures how often the classifier makes the correct predictions, as it is the ratio between the number of correct predictions and the total number of predictions.

2. Precision measures the proportion of predicted Positives that are truly Positive. Precision is a good choice of evaluation metrics when you want to be very sure of your prediction. For example, if you are building a system to predict whether to decrease the credit limit on a particular account, you want to be very sure about the prediction or it may result in customer dissatisfaction.

The confusion matrix (or confusion table) shows a more detailed breakdown of correct and incorrect classifications for each class. Using a confusion matrix is useful when you want to understand the distinction between classes, particularly when the cost of misclassification might differ for the two classes, or you have a lot more test data on one class than the other. For example, the consequences of making a false positive or false negative in a cancer diagnosis are very different.

Convolution Neural Networks-In the past few decades, Deep Learning has proved to be a very powerful tool because of its ability to handle large amounts of data. The interest to use hidden layers has surpassed traditional techniques, especially in pattern recognition. One of the most popular deep neural

networks is Convolution Neural Networks. Since the 1950s, the early days of AI, researchers have struggled to make a system that can understand visual data. In the following years, this field came to be known as Computer Vision. In 2012, computer vision took a quantum leap when a group of researchers from the University of Toronto developed an AI model that surpassed the best image recognition algorithms and that too by a large margin.

The AI system, which became known as Alex Net (named after its main creator, Alex Krizhevsky), won the 2012 Image Net computer vision contest with an amazing 85 percent accuracy. The runner-up scored a modest 74 percent on the test. At the heart of Alex Net was Convolutional Neural Networks a special type of neural network that roughly imitates human vision. Over the years CNNs have become a very important part of many Computer Vision applications and hence a part of any computer vision course online. So let's take a look at the workings of CNNs.

CNN: In deep learning [9], a convolution neural network (CNN/ConvNet)[10] is a class of deep neural networks[11], most commonly applied to analyze visual imagery. Now when we think of a neural network we think about matrix multiplications but that is not the case with ConvNet. It uses a special technique called Convolution. Now in mathematics convolution is a mathematical operation on two functions that produces a third function that expresses how the shape of one is modified by the other. Background of CNNs-(CNN's) were first developed and used around the 1980s. The most that a CNN could do at that time was recognizing handwritten digits. It was mostly used in the postal sectors to read zip codes, pin codes, etc. The important thing to remember about any deep learning model is that it requires a large amount of data to train and also requires a lot of computing resources. This was a major drawback for CNNs at that period and hence CNNs were only limited to the postal sectors and it failed to enter the world of machine learning **SVM-**A support vector machine (SVM[12]) is a type of supervised learning algorithm used in machine learning to solve classification and regression tasks; SVMs are particularly good at solving binary classification problems, which require classifying the elements of a data set into two groups.

The followings are important concepts in SVM:

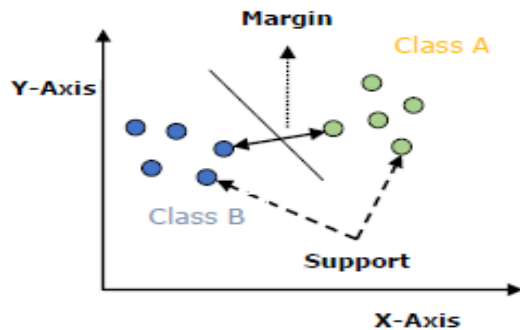
1) **Support Vectors** – Data points that are closest to the hyper plane is called support vectors. Separating line will be defined with the help of these data points.

2) **Hyper plane** – As we can see in the above diagram, it is a decision plane or space which is divided between a set of objects having different classes.

3) **Margin** – It may be defined as the gap between two lines on the closet data points of different classes. It can be calculated as the perpendicular distance from the line to the support vectors. Large margin is considered as a good margin and small margin is considered as a bad margin.

The aim of a support vector machine algorithm is to find the best possible line, or decision boundary, that separates the data points

of different data classes. This boundary is called a hyper plane when working in high-dimensional feature spaces. The idea is to maximize the margin, which is the distance between the hyper plane and the closest data points of each category, thus making it easy to distinguish data classes.



How do support vector machines work:

The key idea behind SVMs is to transform the input data into a higher-dimensional feature space. This transformation makes it easier to find a linear separation or to more effectively classify the data set.

To do this, SVMs use a kernel function. Instead of explicitly calculating the coordinates of the transformed space, the kernel function enables the SVM to implicitly compute the dot products between the transformed feature vectors and avoid handling expensive, unnecessary computations for extreme cases.

SVMs can handle both linearly separable and non-linearly separable data. They do this by using different types of kernel functions, such as the linear kernel, polynomial kernel or radial basis function (RBF) kernel. These kernels enable SVMs to effectively capture complex relationships and patterns in the data.

During the training phase, SVMs use a mathematical formulation to find the optimal hyper plane in a higher-dimensional space, often called the kernel space. This hyper plane is crucial because it maximizes the margin between data points of different classes, while minimizing the classification errors. The kernel function[13] plays a critical role in SVMs, as it makes it possible to map the data from the original feature space to the kernel space. The choice of kernel function can have a significant impact on the performance of the SVM algorithm; choosing the best kernel function for a particular problem depends on the characteristics of the data. Some of the most popular kernel functions for SVMs are the following:

- Linear kernel.-This is the simplest kernel function, and it maps the data to a higher-dimensional space, where the data is linearly separable.
- Polynomial kernel.-This kernel function is more powerful than the linear kernel, and it can be used to

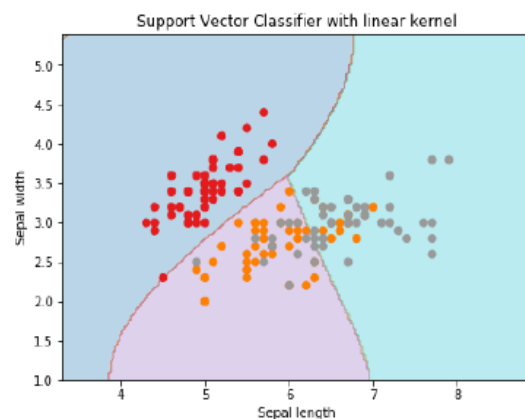
map the data to a higher-dimensional space, where the data is non-linearly separable.

- RBF kernel-This is the most popular kernel function for SVMs, and it is effective for a wide range of classification problems.
- Sigmoid kernel- This kernel function is similar to the RBF kernel, but it has a different shape that can be useful for some classification problems.

The choice of kernel function for an SVM algorithm is a tradeoff between accuracy and complexity. The more powerful kernel functions, such as the RBF kernel, can achieve higher accuracy than the simpler kernel functions, but they also require more data and computation time to train the SVM algorithm. But this is becoming less of an issue due to technological advances. Once trained, SVMs can classify new, unseen data points by determining which side of the decision boundary they fall on. The output of the SVM is the class label associated with the side of the decision boundary.

$$K(x, x_i) = \sum(x * x_i)$$

$$K(x, x_i) = \exp(-\gamma \sum(x - x_i)^2)$$



Types of support vector machines

Linear SVM-Linear SVMs use a linear kernel to create a straight-line decision boundary that separates different classes. They are effective when the data is linearly separable or when a linear approximation is sufficient. Linear SVMs are computationally efficient and have good interpretability, as the decision boundary is a hyper plane in the input feature space

.Linear Kernel-It can be used as a dot product between any two observations. The formula of linear kernel is as below

$$K(x, x_i) = \sum(x * x_i)$$

Non linear SVM. Nonlinear SVMs address scenarios where the data cannot be separated by a straight line in the input feature space. They achieve this by using kernel functions that implicitly map the data into a higher-dimensional feature space, where a linear decision boundary can be found. Popular kernel functions used in this type of SVM include the polynomial kernel, Gaussian (RBF) kernel and sigmoid kernel. Nonlinear SVMs can capture complex patterns and achieve higher classification accuracy when compared to linear SVMs.

$$\min_{w,b,\beta_n} \frac{1}{2} \|w\|_2^2 + C \sum_n \beta_n$$

$$s. t. \quad y_n [w^T \phi(x_n) + b] \geq 1 - \beta_n; \quad \forall n$$

$$\beta_n \geq 0, \quad \forall n$$

CNN Algorithm	
Convolution	$z^l = h^{l-1} * W^l$
Max Pooling	$h^l_{xy} = \max_{i=0..s, j=0..s} h^{l-1}(x+i)(y+j)$
Fully-connected layer	$z_l = W_l * h_{l-1}$
ReLu(Rectifier)	$\text{ReLU}(z_l) = \max(0, z_l)$
Softmax	$\text{softmax}(z_l) = e^{z_l} / \sum_j e^{z_j}$

$$n_{out} = \left\lfloor \frac{n_{in} + 2p - k}{s} \right\rfloor + 1$$

$$j_{out} = j_{in} * s$$

$$r_{out} = r_{in} + (k - 1) * j_{in}$$

$$start_{out} = start_{in} + \left(\frac{k - 1}{2} - p \right) * j_{in}$$

IV.MACHINE LEARNING

Machine learning [14] is a branch of artificial intelligence (AI) and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy.

IBM has a rich history with machine learning. One of its own, Arthur Samuel is credited for coining the term, “machine learning” with his research (PDF, 481 KB) (link resides outside IBM) around the game of checkers. Robert Nealey, the self-proclaimed checkers master, played the game on an IBM 7094 computer in 1962, and he lost to the computer. Compared to what can be done today, this feat almost seems trivial, but it’s considered a major milestone within the field of artificial intelligence. Over the next couple of decades, the technological developments around storage and processing power will enable

some innovative products that we know and love today, such as Netflix’s recommendation engine or self-driving cars.

Machine learning is an important component of the growing field of data science. Through the use of statistical methods, algorithms are trained to make classifications or predictions, uncovering key insights within data mining projects.

These insights subsequently drive decision making within applications and businesses, ideally impacting key growth metrics. As big data continues to expand and grow, the market demand for data scientists will increase, requiring them to assist in the identification of the most relevant business questions and subsequently the data to answer them.

Machine Learning vs. Deep Learning vs. Neural Networks

Since deep learning [15] and machine learning tend to be used interchangeably, it’s worth noting the nuances between the two. Machine learning, deep learning, and neural networks are all sub-fields of artificial intelligence. However, deep learning is actually a sub-field of machine learning, and neural networks are a sub-field of deep learning.

The way in which deep learning and machine learning differ is in how each algorithm learns. Deep learning automates much of the feature extraction piece of the process, eliminating some of the manual human intervention required and enabling the use of larger data sets. You can think of deep learning as “scalable machine learning” as Lex Fridman notes in this MIT lecture (link resides outside IBM). Classical, or “non-deep”, machine learning is more dependent on human intervention to learn. Human experts determine the set of features to understand the differences between data inputs, usually requiring more structured data to learn.

“Deep” machine learning can leverage labelled datasets, also known as supervised learning, to inform its algorithm, but it

Doesn’t necessarily require a labelled dataset. It can ingest unstructured data in its raw form (e.g. text, images), and it can automatically determine the set of features which distinguish different categories of data from one another. Unlike machine learning, it doesn’t require human intervention to process data, allowing us to scale machine learning in more interesting ways. Deep learning and neural networks are primarily credited with accelerating progress in areas, such as computer vision, natural language processing, and speech recognition.

Neural networks[16], or artificial neural networks (ANNs), are comprised of a node layers, containing an input layer, one or more hidden layers, and an output layer. Each node, or artificial neuron, connects to another and has an associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the network. The “deep” in deep learning is

just referring to the depth of layers in a neural network. A neural network that consists of more than three layers—which would be inclusive of the inputs and the output—can be considered a deep learning algorithm or a deep neural network. A neural network that only has two or three layers is just a basic neural network.

Machine Learning Methods

Machine learning classifiers fall into three primary categories.

1) *Supervised machine learning:*

Supervised learning[17], also known as supervised machine learning, is defined by its use of labeled datasets to train algorithms that to classify data or predict outcomes accurately. As input data is fed into the model, it adjusts its weights until the model has been fitted appropriately. This occurs as part of the cross validation process to ensure that the model avoids over fitting or under fitting. Supervised learning helps organizations solve for a variety of real-world problems at scale, such as classifying spam in a separate folder from your inbox. Some methods used in supervised learning include neural networks, naïve bayes, linear regression, logistic regression, random forest, support vector machine (SVM), and more.

2) *Unsupervised machine learning:*

Unsupervised learning[18], also known as unsupervised machine learning, uses machine learning algorithms to analyze and cluster unlabeled datasets. These algorithms discover hidden patterns or data groupings without the need for human intervention. Its ability to discover similarities and differences in information make it the ideal solution for exploratory data analysis, cross-selling strategies, customer segmentation, image and pattern recognition. It's also used to reduce the number of features in a model through the process of dimensionality reduction; principal component analysis (PCA) and singular value decomposition (SVD) are two common approaches for this. Other algorithms used in unsupervised learning include neural networks, k-means clustering, probabilistic clustering methods, and more.

Semi-supervised learning:

Semi-supervised learning offers a happy medium between supervised and unsupervised learning. During training, it uses a smaller labeled data set to guide classification and feature extraction from a larger, unlabeled data set. Semi-supervised learning can solve the problem of having not enough labeled data (or not being able to afford to label enough data) to train a supervised learning algorithm.

3) *Reinforcement Machine Learning*

Reinforcement machine [19] learning is a behavioral machine learning model that is similar to supervised learning, but the algorithm isn't trained using sample data. This model learns as it goes by using trial and error. A sequence of successful outcomes will be reinforced to develop the best recommendation or policy for a given problem.

DATASET

A **dataset** Is a collection of data in which data is arranged in some order. A dataset can contain any data from a series of an array to a database table. Below table shows an example of the dataset:

A tabular dataset can be understood as a database table or matrix, where each column corresponds to a particular variable and each row corresponds to the fields of the dataset. The most supported file type for a tabular dataset is "Comma Separated File," or CSV. But to store a "tree-like data," we can use the JSON file more efficiently. Types of data in datasets.

Dataset in Machine Learning

A single row of data is called an instance. Datasets are a collection of instances that all share a common attribute. Machine learning models will generally contain a few different datasets, each used to fulfil various roles in the system.

For machine learning models to understand how to perform various actions, training datasets must first be fed into the machine learning algorithm, followed by validation datasets (or testing datasets) to ensure that the model is interpreting this data accurately.

Once you feed these training and validation sets into the system, subsequent datasets can then be used to sculpt your machine learning model going forward. The more data you provide to the ML system, the faster that model can learn and improve.

V.METHODS

Array scalars have exactly the same methods[20] as arrays . The default behaviour of these methods is to internally convert the scalar to an equivalent 0-dimensional array and to call the corresponding array method. In addition, math operations on array scalars are defined so that the same hardware flags are set and used to interpret the results as for ufunc, so that the error state used for ufuncs also carries over to the math on array scalars.

DATA TYPE OBJECTS (DTYPE)

A data type object (an instance of numpy. dtype class) describes how the bytes in the fixed-size block of memory corresponding to an array item should be interpreted [18]. It describes the following aspects of the data:

1. Type of the data (integer, float, Python object, etc.)
2. Size of the data (how many bytes is in e.g. the integer)
3. Byte order of the data (little-endian or big-endian)
4. If the data type is structured, an aggregate of other data types, (e.g., describing an array item consisting of an integer and a float),
 - (a) what are the names of the "fields" of the structure, by which they can be accessed,

- (b) what is the data-type of each field, and
(c) which part of the memory block each field takes.

5. If the data type is a sub-array, what is its shape and data type. To describe the type of scalar data, there are several built-in scalar types in Numpy for various precision of integers, floating-point numbers, etc.

An item extracted from an array, e.g., by indexing, will be a Python object whose type is the scalar type associated with the data type of the array. Note that the scalar types are not dtype objects, even though they can be used in place of one whenever a data type specification is needed in Numpy. Structured data types are formed by creating a data type whose fields contain other data types. Each field has a name by which it can be accessed. The parent data type should be of sufficient size to contain all its fields; the parent is nearly always based on the void type which allows an arbitrary item size. Structured data types may also contain nested structured sub-array data types in their fields. Finally, a data type can describe items that are themselves arrays of items of another data type. These sub-arrays must, however, be of a fixed size. If an array is created using a data-type describing a sub-array, the dimensions of the sub-array are appended to the shape of the array when the array is created. Sub-arrays in a field of a structured type behave differently, see Field Access. Sub-arrays always have a C-contiguous memory layout.

Result& Discussion

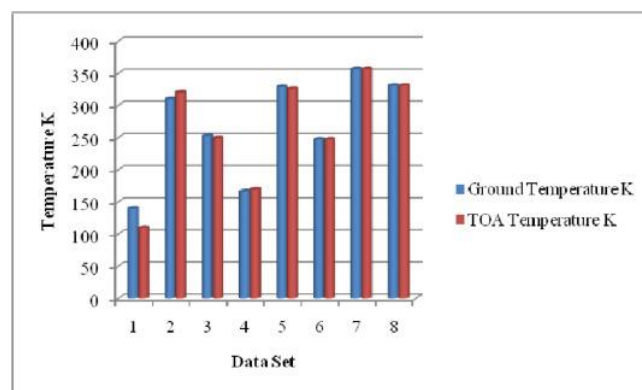
In this section the experimental results are discussed and the performances are evaluated. The proposed method is applied to various set of Land sat images and CNN Algorithm Technique is used for prediction. The Land area and the prediction area should be differentiated from the band after calculating the Temperature (Land Areas-Red, Prediction Area-Yellow). Then the prediction areas in which temperature is greater than 300 K are differentiated by Yellow and the unused areas as Black after calculating the temperature values. Some set of images the intensity values are calculated for each pixel [21]. The set of intensity values are used to train the dataset whether forest fire is found or not. Finally, the highest intensity values should be calculated for that band. The threshold for fire based on intensity is more than 150. CNN classification is the process of grouping elements into a CNN set whose membership function is defined by the truth value of a fuzzy propositional function. Based on the Ground, TOA temperature and the intensity values the Forest sets are classified using CNN classification [22]. The Forest Fire and the normal images are considered to find the temperature in the specified area. The datasets are collected from the website www.usgs.gov. Forest area was taken to predict the forest fire. The datasets are collected before and after forest fire [23]. This proposed technique was used to detect the forest fire using the temperature (TOA and Ground) and intensity values. The unused areas are identified and the remaining areas are taken to predict the forest fire. T1, T2, T3, T8 are the bands used to predict the forest fire as shown in Table 3.

Table 3. Landsat Thermal Band Temperature and intensity values.

Band	Land area count	Prediction area count	Ground Temperature K	TOA Temperature K
T1	331697	22438	140.6045	110.1442
T2	325595	30408	310.8436	321.0228
T3	288029	59186	252.7034	249.439
T4	292028	56358	166.7463	169.9417
T5	148587	41275	329.674	326.642
T6	316530	38693	247.362	247.362
T7	376029	36002	357.1242	357.1242
T8	389689	36045	331.6986	331.6888

Fig. 2 shows the analysis about TOA and Ground Temperature. The images are collected from Landsat-7 and Landsat-8 sensors. The Fire areas are calculated based on the intensity values of the pixels. Greater intensity values are used to calculate the temperature in the area. The values are projected in the Table 3. UCC values [[24], [25], [26]] are used to calculate the intensity values in the area. The threshold values are fixed based on the temperatures calculated from the bands. The highest temperature is found

As 300 K. Thus, the forest fire is predicted if the temperature is greater than 300K.



VI.CONCLUSION

While gas sensing technology involves highly complicated design, invention, and operational features, artificial intelligence may aid in addressing these challenges. In this study, a soft-sensing method was introduced for the precise estimates of a NO₂ gas sensor using AI computations. Sensitivity/response time is introduced according to forecasting both sensitivity and response time. The present research suggests the application of met heuristics algorithms for the online optimization of the gas sensing process, whereas the deep learning algorithm application for the prediction of sensitivity/response time can be attractive for other investigations.

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