Mobility-Compliant Model in Drone-Based Sniffing Technique for Aerial Surveillance and Security

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***Abstract*—Security threats in the aviation sector and across countries' borders are culpable by chemical explosives and improvised explosive devices (IED). Remotely detecting traces of these chemicals limits the statistics of explosions worldwide. To proffer a security solution, this paper proposed the use of a laser-radar-equipped drone with an embedded deep neural model for artificial sniffing of the different compositions of chemical explosives. The accuracy, sensitivity, and computation cost values of 94.5%, 94%, and 4.1% respectively, indicate a robust system for real-time surveillance of operational environments.**

***Index Terms*—Artificial neural network, Chemical explosives, Drones, Electronic nose, Sniffing Technique.**

I. Introduction

Due to the escalating terrorism situation, the efficient and accurate detection of explosives has become an upsurge in demand for the entire world. The threat of the usage of chemical explosives in airports and their transportation across countries' borders are continually evolving. Also, the number of high-profile attacks aided by these chemicals has been on the increase causing devastating outcomes and unrest in the world. These explosives can be detected in bulk or as traces of residues. Recent research is focused on detecting the traces of these deadly chemicals to limit casualties mostly in public places.

However, explosive detectors deploy in airports and borders are location-based; that is, requiring proximity to the explosive molecules. Swab technique, scanners, ion-spectrometry, X-ray machines, and explosive detection dogs, operate by ingesting the explosives via their detectors and sampling the individual molecular properties [1]. Ineffectiveness when there is a molecular separation of these chemicals, inaccuracy in detecting improvised explosive devices (IED) (because they are manufactured with non-standard chemical compositions, which are the illicit combination of different compounds), and huge threats to explosive trace detection (ETD) operators, are the limitations of location-based ETD systems [2]. Hence, the quest for designing enhanced remote ETD systems to improve national security.

Chemical explosives are composed of either nitrate-based compounds and/or non-nitrate based. Moreover, high explosives are a close combination of an oxidant and a reductant, either contained within a single molecule. Like nitroglycerin, pentaerythritol tetranitrate (PETN), trinitrotoluene (TNT), or triacetone triperoxide (TATP) or within an ionic solid like ammonium nitrate when combined with fuel oil, also called ammonium nitrate fuel oil (ANFO). High explosives or detonating explosives such as TNT, ANFO, TATP, and nitroglycerin are a class of explosives characterized by their rapid decomposition and development of high pressure. These explosives either detonate when ignited by a flame or means that produce enough heat, or via a detonator. Most nitrate, chlorate, sodium, ammonium compounds, and some hydrogen peroxides are precursors of chemical explosives, making their illicit mixture with other chemical compounds lethal. Therefore, mechanisms that require no contact with these dangerous chemicals before predicting their explosive nature are advantageous to the safety of lives and properties. Nevertheless, remote technology and artificial intelligence are feasible solutions.

The artificial sniffing technique seeks to imitate either a human or an animal's sense of smell, via automation in the timely and accurate predictions of hazardous chemicals and microbial content of defined samples with even greater sensitivity than a mammal's nose [3]. This innovation also referred to as the electronic nose (e-nose), investigates the biological olfactory function and has found usefulness in a variety of fields, including homeland security, forensics, the food industry, security, etc. Machine learning (ML) algorithms have been pivotal in the designing of e-nose. For instance, authors in [1] designed an e-nose based on artificial neural networks (ANN) for the detection of nitrate-based explosives and the classification of food. However, only nitrate-based chemical explosives were considered. Also, a ship exhaust sniffing drone system was designed in [4]. The system aided in the real-time monitoring of the emission of fuel sulfur content and the screening of vessel compliance to reduce air pollutants. Neglect of the model's computational cost is a major drawback, considering the resource-constraint nature of drones [5], [6].

The goal of this research is to design an ML model based on ANN with maximum accuracy, sensitivity, and minimum computational cost while leveraging the remote sensing capability of a laser-radar-equipped drone for real-time ETD of both nitrate and non-nitrate-based explosive chemicals deployed in airports and country borders.

II. System Methodology

The artificial nose has the canine-like ability facilitated by absorption spectroscopy to sniff out explosives from the vapor plume from a distance. The airflow, particulate matter, chemical explosives, and other air pollutants, can all be detected with the laser radar drone on which the e-nose is envisioned to be mounted.

This sensor drone as captured in Fig. 1, is expected to hover around the airport or border in search of gamma rays or other hazardous particles, and based on the heuristic of the neural network embedded in it, compares the specific vapor and makes predictions. When traces of chemical explosives are $sniffed$ the drone triggers an alert at the control station (CS) for appropriate decisions. The architectural framework of the proposed deep neural network (DNN) serving as the baseline algorithm is depicted in Fig. 1 for the real-time detection and prediction of chemical explosives. The DNN is comprised of three distinct layers, that is, the input, hidden, and output layers.

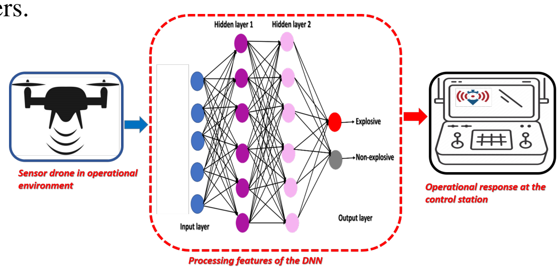

Fig. 1: Proposed Sniffing System

The input layer is fed with the different nitrate, ammonium, sodium compounds and other particulate matter sniffed by the sensor drone. In addition, in the hidden layer where all the computations are done (weighted average and bias adjustments) is designed with 6 neurons each (hidden layers 1 and 2). Mathematically, equation 1 simplifies the model logic for decision-making based on inference results.

$$y = b_0 + b_1x_1 + b_2x_2 + ... + b_nx_n, \tag{1}$$

where y is the predicted value of the input variables, b_0 is the y intercept, x_1, x_2, $...x_n$ are the input features; b_1, b_2, $...b_n$ are the coefficients of x variables. Given a predefined pressure threshold (θ = 101.325kpa), the value of y is compared with θ value to determine the detection categorization; "explosive" or "non-explosive". Therefore, the prediction of the presence of chemical explosives in a given vicinity will trigger an alarm by the drone, coupled with the exact location at the CS.

A. *Dataset Description*

19 independent variables constitute the features of the dataset used for the training and evaluation of the proposed model gotten from [7]. 2632 instances and 2 target classes of "Explosive" and "Non-explosive" were used for a binary classification task. Hyperparameters utilized for modeling a robust model include; an epoch of 200 iterations, varying batch sizes of 16 and 32, and rectified linear unit and sigmoid as activation functions for the hidden and output layers respectively. Lastly, the stochastic gradient descent (SGD) optimization algorithm and the binary-cross entropy as the loss function was used after standardizing and splitting the dataset in an 80:20 ratio in a Python environment with Tensorflow 2.9.0 on a Windows 10 OS with the configuration of Intel(R) Core(TM) i5-7400 CPU @ 3.00GHz, 8GB RAM, GPU Tesla K80.

B. *Result Discussion*

The results obtained by the proposed model are highlighted in Table I. SGD and Adams optimizers were alternated as well as different batch sizes of 16 and 32. From Table I, it can be gotten that there is a tradeoff between accuracy and the computational cost based on the CPU utilization time. Overall, the model with high sensitivity and least cost was achieved by the SGD optimizer having a batch size of 32, accuracy, recall (sensitivity), F1-score, and CPU time of 94.5%, 94%, 93%, and 4.1% respectively.

TABLE I: Performance Results of Proposed Model

Optimizer	Batch size	Epoch	Accu. (%)	Recall (%)	F1-score (%)	CPU time(%)
SGD	**32**	**200**	94.5	**94**	**93**	**4.1**
SGD	16	200	93.7	91	91	5.8
Adam	32	200	**95**	91	91	6.2
Adan	16	200	93.5	91	91	3.3

Correspondingly, the accuracy and loss graphs are captured in Fig.2.

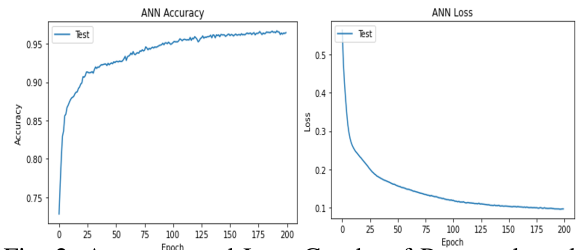

Fig. 2: Accuracy and Loss Graphs of Proposed model

III. Conclusion

The timely and accurate detection of chemical explosives in operational environments is paramount for national security. To reduce the casualties experienced in airports and borders aided by these chemicals, the utilization of a laser-radar drone embedded with a deep neural model for artificial sniffing and prediction was investigated. The sensitivity and accuracy results achieved by the model are suitable for real-time surveillance, thus fostering robust security.

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