International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

A Spatial Analysis Model for Proactive Assessment on Radioactive Isotopes in Environment

[1]K. Revathi, [2]T. Tamilselvi, [3]P. Karpagam, [4]M. Dhivya
[1]Department of Artificial Intelligence and Data Science,
Dhanalakshmi College of Engineering,
Chennai, India - 601301
neyadharshini@gmail.com / revathi.k@dce.edu.in
[2]Department of Computer Science and Engineering,
SRM Institute of Science and Technology – Ramapuram Campus,
Chennai, India - 600089
tamilselvime@gmail.com
[3]Department of Cyber Security,
Dhanalakshmi College of Engineering,
Chennai, India - 601301
karpagamp.ai@dce.edu.in
[4]Department of Computer Science and Engineering,
Panimalar Engineering College,
Chennai, India - 600123
dhivyachweetu@gmail.com

Abstract— In general, no one can escape from radiation. Radiation exists in various forms as minerals in earth and water, cosmic rays in space, radioactive energy in human body, man-made effects as in the form of industrial waste, result of nuclear weapon test, nuclear reactor and medical procedures. The people those who are living closer to the environment where radioactive emission is found to be high, would have a high risk of getting significant health aliments like skin burns and radiation sickness. Moreover people who receive constant exposure to lower level of radiation will susceptible to have cancer and cardio vascular diseases in their life time. The primary motive of the proposed work is to evaluate the concentration of the radioactivity substances, tracking the impact through present and futuristic patterns using deep learning techniques.

Keywords- deep learning; environmental monitoring; proactiveness; radioactivity; spatial analysis

I. Introduction

Humans are unable to detect it with their five senses, because radiation has no smell and is invisible. It does have one function, though, that makes measurement simple. The radiation-related units "Becquerel" and "Sievert," about which we have heard a lot lately, are linked. For instance, the amount of radioactive elements present in food or soil can be determined by measuring their radiation using a specialized instrument. The unit used to express the intensity of this kind of radiation is the Becquerel. A unit used to express the impact on the human body is the Sievert [1].

A handheld survey meter can be used to locate areas that are highly radioactively contaminated. Survey meters of different kinds can also be used to measure radioactivity types and intensities released by radioactive elements alongside individual exposure levels.

Furthermore, radiation doses resulting from the accident's effects and natural radiation doses, as well as their combined amounts, can be determined independently based on the findings of several investigative research.

According to the report of National Council on Radiation Protection and Measurements (NCRP) in 2006, every human in the United States (U.S.) is realized to consume 6.2 millisieverts as average in a year of time [2]. Among all other contributors of radionuclides, the presence of radioactive gases like radon and thoron in environment preserves high percentage as 37%. The nuclear reactors are not the major source that emits radioactivity materials. The radiation isotopes such as uranium, thorium and its by-products are 100 times more vulnerable than nuclear power plant emissions. This necessitates intelligent geospatial analysis model to predict the radiation impact around its environment of interest. The Vallur power station which is coal based plant, located in Tamil Nadu produced 1500 MW out of 48,120 MW capacity realized among the other 23 stations installed all over India [3]. This induces to design a proactive solution to assess and control radiation using modern technologies like remote sensing, geographical information system (GIS), artificial intelligence and machine learning algorithms.

In aligned with the gamma ray spectroscopy technique, using radiation detectors such as semiconductor (HPGe)detectors, crystal scintillator detectors and Sodium oxide NaI(TI) detector, can be used to detect the radioactive substances in the environment. Among other choices of detectors, thallium-doped sodium iodide detector, NaI(Tl), is a common choice as a portable detector because of its reasonable cost. However, NaI detectors have relatively weak energy resolution and temperature dependence, which makes it weak to resolve many of the photo peaks in a spectrum.

Ensuring the long-term viability and efficacy of radiation-related operations while safeguarding the environment and public health is the aim of radiological sustainability. It entails taking into account all aspects of radiation sources' life cycles, including their creation, use, disposal, and handling of related wastes [4]. The primary motive of the proposed project is to evaluate the concentration of the radioactivity substances, tracking the impact through present and futuristic patterns. The paper which in turn aimed to reduce related health issues and prohibit major accidental events in future.

II. LITERATURE REVIEW

This section details the exceptional contributions that have been made by several researchers in finding practical ways to identify radioactive materials.

A. *Related Work*

Norasalwa et al. and Zeevaert et al. [5, 6] revealed the effect of radiological emissions in their study. The coal-fired power plants are identified as a significant contributor of radiological wastes and impact the environment health comparatively more than the nuclear technologies.

Fernandez et al. [7] conducted an exhaustive survey to bring out intelligent data driven applications that ensures safety in nuclear power plant operations like assessing the health of nuclear reactor, detecting the level of radiation and optimizing the productive tasks. The authors summarized the risks associated with nuclear reactors, radiation and its impact towards society. They also elaborated the significant role of data analytics in this domain.

Mohammed Saeed et al. [8] delivered a Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model that predicts the radiation impact around Baiji site. The suitability of nuclear power plant installation upon ensuring human and environmental health is assessed in their work.

Luís Marques et al. [9] investigated the need of portable monitoring devices in assessing the radioactive materials in their study. They evaluated the usage of such monitors against different scenario of nuclear industries.

Xingang Zhao e al. [10] conducted a deep survey on data-driven methods in diagnosing the health of the nuclear power plants. The scope for machine learning algorithms in assessment and validation of the various activities of plant is highlighted in the article.

Jacqueline S. Chaplow et al [11] carried out inherent survey on dispersion of radionuclides in and around Chernobyl nuclear power plant. They investigated the role of spatial model in analyzing the same. Also composed and contributed a data set that serves for radiation detection.

Pingo Tang et al. [12] developed a video based analysis model through incorporating computer vision algorithms for predicting outage of nuclear waste. The model was built to effectively maintain the aging nuclear power plant's activities of the U.S. The system was designed to capture the abnormal activities of workers and long delay caused like this type of attitude of the worker. The simulation results produced out of this work concluded that unplanned schedule, untrained and lack of committed workers were the main cause.

Hang Wang et al. [13] devised a monitoring system that continually the tracks he component such reactor valve of nuclear power plants for its smooth conduct of operation. They employed temporal convolutional neural network to accurately predict the functionalities of valves. Upon receiving anomaly condition initiates evacuation plans in advance.

Habib Zaidi et al. [14] summarized the primary applications of artificial intelligence (AI), particularly deep learning methodologies, in molecular imaging and radiation therapy research .To this goal, artificial intelligence applications in five general disciplines like molecular imaging and radiation therapy, image quantification and segmentation, image denoising (low-dose imaging), radiation dosimetry, computer-assisted diagnostics, and prediction is discussed.

While many applications emphasize the accuracy of the learning algorithm's prediction, practice has shown that these algorithms are prone to learning non-descriptive or irrelevant properties. As a result, Gomez-Fernandez et al. [15] turned focus of their research is on deciphering the reasons behind the classification utilizing saliency approaches. The end-user can evaluate the performance based on domain knowledge by looking at visual representations of the network's learned regions of interest to see if domain-specific properties are being detected.

Lee et al. [16] proposed method that outperformed the most recent state-of-the-art models. The advantages and disadvantages of linked, recurrent, convolutional, and gradient boosted decision trees are examined under a range of testing situations. Furthermore, by integrating the fully-connected and convolutional neural networks, a hybrid model is created, which has the best performance (93.33%) among the various machine learning models.

Ghawaly Jr et al. [17] composed dataset depicting the movement of a NaI(Tl) scintillation detector in a simulated urban environment based on Knoxville, Tennessee which can be used for radioisotope identification.

B. *Research Objectives*

The key objectives are as follows:

1. To facilitate the regular monitoring of radioactive substances in environment
2. To realize the intelligent prediction models using deep learning mechanisms
3. To provide efficient real time application to assess radioactive isotopes and in turn to evaluate necessary control plans to avoid major disasters in a proactive manner

III. PROPOSED SYSTEM

Building accurate and automotive radiation detection system is not an easier task. It involves significant collection of data pertaining atmospheric conditions from environment. By testing current weather model against the observed radiation pattern only detect futuristic radiation pattern and its regional impact. After obtaining the dataset, the proposed work exercises deep learning based analysis to project radioactive materials and predict extreme events in early stage. Thus the major activities of proposed system are categorized as follows:

A. *Ascertaining a Dataset*

This work is attempted to gather the data pattern in order to forecast the impact of radiation. The proposed dataset combines the weather pattern along with monitored radiation impact observed at specific region of interest to deliver an efficient analysis model.

Real time data set, a dataset consisting of realistic Monte Carlo–simulated radiation detection data from a 2 in. × 4 in. × 16 in. is utilized in this work. The dataset was developed by using a NaI(Tl) scintillation detector moving through a simulated urban environment based on Knoxville, Tennessee, and made public in the form of a Topcoder competition [17].

B. Applying Data Pre-processing

In order to prepare the data for analytics, this phase must first remove noise using the relevant methods mentioned below:

• Filtering

The procedure is to purge and eliminate loud structures from it.

• Feature Extraction

Relevant features are incorporated into the dataset to improve the classification outcome via feature extraction. Hierarchical clustering PCA (HCPCA), a version of principal component analysis (PCA), is intended to be used for efficient feature extraction [18].

C. Predicting Futuristic Trends using Deep Learning

The optimized input data are imported to the server to enable data storage and analytics process. The deep learning techniques are exercised here to reduce the error rate in classification. The advantages of deep learning algorithms are listed below.

- One of the key benefits of deep learning is its ability to solve complex issues that necessitate the discovery of hidden patterns in data and/or a thorough knowledge of complex relationships among a large number of interdependent variables.
- While deep learning eliminates the need for humans to perform feature engineering because the machine does it for them, it also makes it more difficult for humans to understand and interpret the model.
- When evaluating any machine learning model, a tradeoff between accuracy and interpretability must usually be made. In many sectors, deep networks have attained accuracy well above that of traditional machine learning approaches, yet they are practically impossible to interpret since they mimic exceedingly complicated scenarios with strong nonlinearity and interactions between inputs.

Convolutional neural networks, or CNNs, are deep learning algorithms that have garnered attention recently due to their effectiveness in mapping large amounts of images in a short amount of time. To improve the prediction accuracy, the result set can be further optimized by using a particle swarm optimization (PSO). The schematic representation of how the proposed methodologies are incorporated is presented as figure 1 as given below.

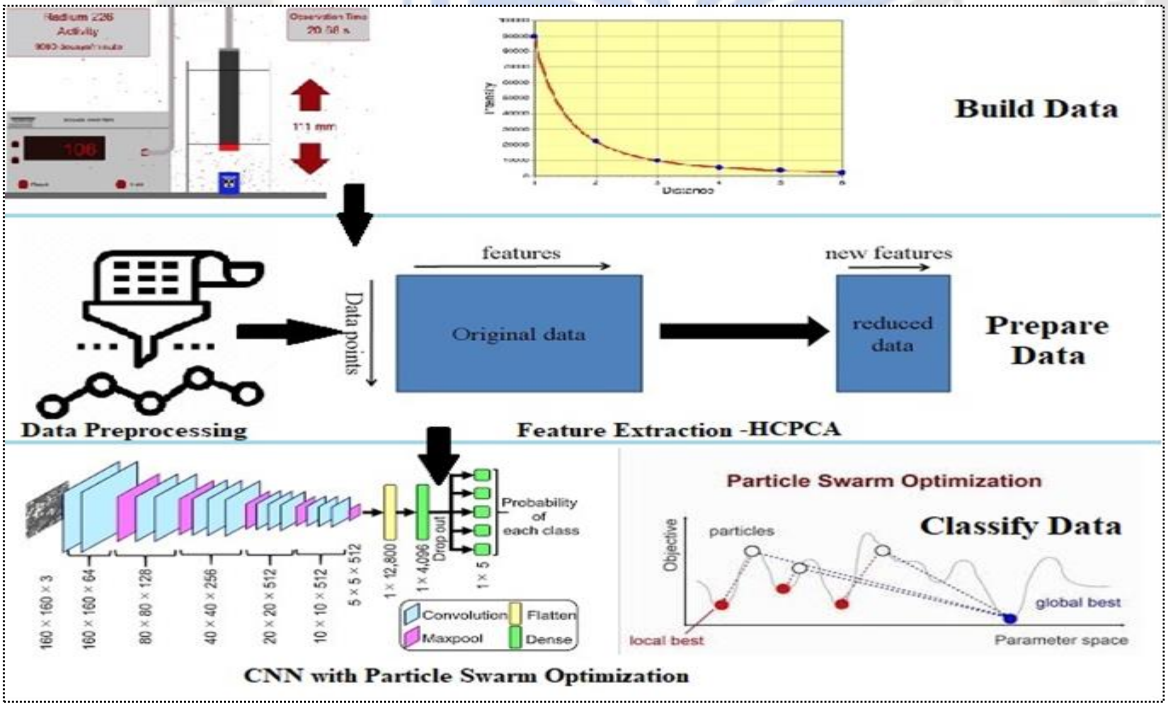

Figure 1. Shematic diagram of proposed model in detecting radiactive elements.

The intelligent collective action of naturally occurring social swarms serves as a foundation for Swarm Intelligence (SI), an important subset of artificial intelligence. The most used SI paradigm is the PSO algorithm. Researchers' interest in PSO has increased as a result of its increasing use in many applications during the past several years [19, 20]. Similar to a flock of birds looking for food, we start with a number of randomly selected points on the plane (we refer to them as particles) and let them hunt in different directions for the minimum point. At each step, each particle should consider its surroundings, including the lowest point it has ever found and

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

the lowest place the entire swarm of particles has ever found. Table 1 illustrates the PSO process flow.

TABLE I. ALGORITHMIC STEPS IN PARTICLE SWARM OPTIMIZATION

[1] Set X_i and V_i such that $x_i \in rand(X^{min}, X^{max})$ and $V_i = 0$ where $rand(X^{min}, X^{max})$ is the uniform random number between X^{min} and X^{max} $(\forall_i = 1,2, \ldots, n)$
[2] $\hat{X}_i \leftarrow X_i \text{ and } \hat{g} \leftarrow \arg\min_{x_i} f(x_i)$
[3] While not converged:
[3.1] For each particle:
- Produce uniform random numbers
- Update the velocities of each particle:

$$V_i^{k+1} \leftarrow \omega v_i^k + c_1 r_1 \left(\hat{x}_i - x_i^k\right) + c_2 r_2 \left(\hat{g} - x_i^k\right)$$

[3.2] Update the positions of each particle:

$$x_i^{k+1} \leftarrow x_i^k + v_i^{k+1}$$

[3.3] Compute $f(x_i)$
[3.4] Update the local bests: $\hat{x}_i \leftarrow x_i \text{ if } f(x_i) < f(\hat{x}_i)$
[3.5] Update the global best: $\hat{g} \leftarrow x_i \text{ if } f(x_i) < f(\hat{g})$

In our opinion, the lowest position ever explored by this swarm of particles is represented by the smallest point of the function, after a certain number of iterations. The metrics c1 and c2, respectively, are referred to as the "cognitive coefficient" and "social coefficient," respectively. They determine the relative value of both identifying the particle's search result and optimizing the swarm's search result. These elements can be considered as affecting the trade-offs between the exploration and exploitation [21]. One interesting feature that distinguishes this technique from other optimization techniques is that it does not depend on a gradient in the desired function. Another advantage of PSO is how simple it is to parallelize.

IV. RESULTS AND DIXCUSSION

This section covers the execution environment, key performance indicators that show how well the suggested deep learning model works, and the evaluation findings in great detail.

A. *Experimetal Setup*

For implementation, the 'global_air_quality' dataset that was taken from Kaggle is utilized. Python environment is chosen as the platform of implementation. Data queries are performed using the Google BigQuery library. When used in conjunction with Google Storage, BigQuery actually a web-based RESTful service that allows for the interactive study of extremely big datasets. It's a kind of Infrastructure as a Service that can work in tandem with MapReduce. Data stored in cloud storage will be converted into a Pandas DataFrame object by the BigQurey Helper Object. The SQL query syntax is the same. Due to the large amount of data, it is difficult to convert the full set to a DataFrame. Therefore, the query is formatted so that visualization may access it easily. The visualization of predicted air quality in India is presented in figure 2.

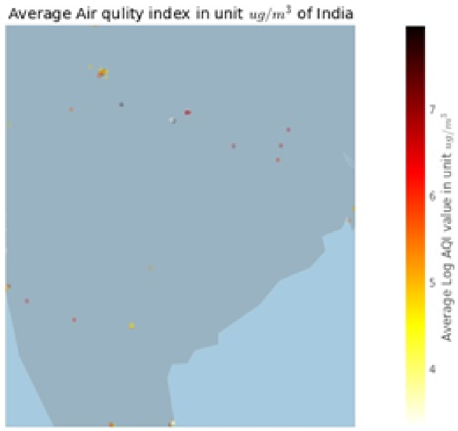

Figure 2. Air quality assessment using the proposed model.

B. *Performance Measures and Evaluation Results*

The following measures of interest are used to evaluate the effectiveness of the proposed model used for radioactive elements analysis and are projected as Table 2 below. These metrics have their roots in the model's confusion matrix. The confusion matrix helps determine whether the model is "confused" in distinctively distinguishing between the two classes. It is commonly displayed as a 2*2 matrix. The column labels in this matrix represent possible anticipated labels, whereas the row labels represent the actual labels. The labels of the two rows and columns are Positive and Negative to represent the two class classifications. The four matrix entries represent the four metrics that measure the number of precise and imprecise predictions the model produced.

- True Positive (TP): The quantity of forecasts that come true
- True Negative (TN): All of the forecasts that are negative
- False Positive (FP): The number of false samples that are projected to be positive but are actually not
- False Negative (FN): The total number of genuine samples that were anticipated to be negative

TABLE II. EVALUATION METRICS

Metric	Formula
Accuracy	$A = \frac{TP+TN}{TP+TN+FP+FN}$
Precision	$P = \frac{TP}{TP+FP}$
Recall	$R = \frac{TP}{TP+FN}$
F-Score	$F = 2*\frac{P*R}{P+R}$

Previous efforts have explored machine learning techniques such as artificial neural network (ANN), support vector machine, and k-nearest neighbor (KNN) algorithms. The fully connected neural network (FCNN), an ANN approach, has demonstrated its effectiveness in improving radiation detection accuracy. This work thus explores the potential of deep learning methods such as CNN empowered with PSO as optimized CNN. Table 3 presents the comparison outcome. The figure 3 provides a clear illustration of the assessment result visualization.

TABLE III. PERFORMANCE ANALYSIS OF PROPOSED MODEL

Models for Evaluation	**Evaluation Metrics**			
	Accuracy	**Precision**	**Recall**	**F-Score**
SVM	81.8	75	83.2	82.3
KNN	84.8	76.5	86.7	85
ANN	87.9	82.4	86.2	85.8
FCNN	88.6	83.7	86.7	86.9
Optimized CNN	98.2	93.3	95.2	95.6

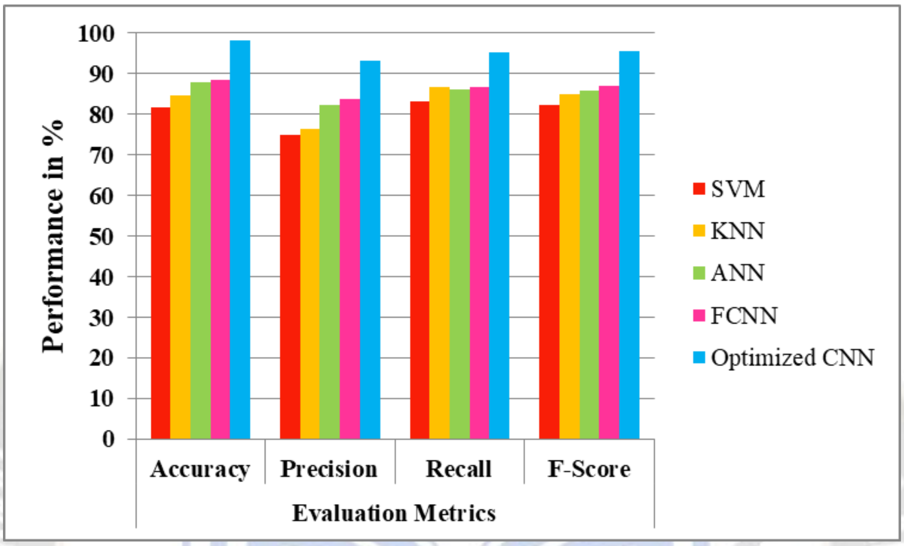

Figure 3. Comparative analysis of radioactive element prediction against proposed deep model.

The findings make it abundantly evident that the proposed deep model (Optimized CNN) was judged to have a promising accuracy rate 98.2 at best. The F-Score, a harmonic mean of precision and recall that gauges overall test accuracy, projects the classifier's or model's precision and durability. The improved accuracy is confirmed by a higher F-Score. Comparing the suggested model to other evaluation methods, the F-Score value is higher, at 95.6%.

V. CONCLUSION

Radiation greatly affects the health of all living organism and degrades the environment's liveliness factor. The proposed project identifies the regional source of radiation, its level or dose and its path of traversal. Through analyzing the spatial data of radiation with weather patterns, one can visualize futuristic trend of radiation. With the predicted result, the accidental events likely to be happened can be avoided. "Preparedness avoids the disasters". Thus the proposed work ensures the preparedness which protects the human and environment health from radiation. The results clearly show that the suggested deep model, called Optimized CNN was found to have a promising accuracy rate of, at most, 98.2.

It is planned to develop a mobile application / web application to further realize the deep learning model over the recipients of interest in future.

ACKNOWLEDGMENT

No funding sources.

AUTHORS CONTRIBUTION

Author 1: Conceptualization, Editing and Experimentation
Author 2: Editing, Experimentation and Supervision
Author 3: Experimentation
Author 4: Editing

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

REFERENCES

[1] Ministry of Environment, Government of Japan, "Booklet to Provide Basic Information Regarding Health Effects of Radiation", First Edition, pp. 33-44, March 2015, https://www.env.go.jp/en/chemi/rhm/basic-info/2018/02.html#anc-02-03.

[2] United States Nuclear Regulatory Commission, "Dose(Radiation)", https://www.nrc.gov/reading-rm/basic-ref/glossary/dose.html, last updated on February 15, 2023.

[3] Power Technology, "Vallur Conventional 1,000MW Thermal Power Plant, India", https://www.power-technology.com/projects/vallurconventional/?cf-view, last updated on February 27, 2015.

[4] A. Shahrokhi, L. Tettey-Larbi, E. O. Akuo-ko, E. Tóth-Bodrogi and T. Kovács, "The New Conception of Radiological Sustainability Possibilities by Reutilization of Residues Products and Building Materials," Sustainability, vol. 15, no. (13):10647, pp. 1-13, July 2023 https://doi.org/10.3390/su151310647

[5] Norasalwa Zakaria, Rohyiza Ba'an and Sivapalan Kathiravale, "Radiological Impact from Airborne Routine Discharges of Coal-Fired Power Plant", RnD Journals, pp. 1-6, October 2010.

[6] Th. Zeevaert, L. Sweeck and H. Vanmarcke,"The radiological impact from airborne routine discharges of a modern coal-fired power plant," Journal of Environmental Radioactivity, vol. 85, no. 1, pp. 1-22, 2006, https://doi.org/10.1016/j.jenvrad.2005.04.015.

[7] M. Gomez-Fernandez, K. Higley, A. Tokuhiro, K. Welter, W. Weng-Keen and H. Yang, "Status of research and development of learning-based approaches in nuclear science and engineering: A review",

Nuclear Engineering and Design, vol. 359, no. 110479, pp. 1-13, April 2020, https://doi.org/10.1016/j.nucengdes.2019.110479.

[8] I. Mohammed Saeed, M. A. Mohammed Saleh, S. Hashim, Y. M. Salih Hama, K. Hamza and S. H. Al Shatri, "The radiological assessment, hazard evaluation, and spatial distribution for a hypothetical nuclear power plant accident at Baiji potential site", Environmental Sciences Europe, vol. 32, no. 6, pp. 1-12, January 2020, https://doi.org/10.1186/s12302-020-0288-8 .

[9] L. Marques, A. Vale and P. Vaz, "State-of-the-Art Mobile Radiation Detection Systems for Different Scenarios", Sensors, vol. 21, no. 4(1051), pp. 1-65, February 2021, pp. 1-65, https://doi.org/10.3390/s21041051.

[10] X. Zhao, J. Kim, K. Warns, X. Wang, P. Ramuhalli, S. Cetiner, H. Gook Kang and M. Golay, "Prognostics and Health Management in Nuclear Power Plants: An Updated Method-Centric Review with Special Focus on Data-Driven Methods", Frontiers in Energy Research, vol. 9, no. 695785, pp. 1-29, June 2021, https://www.frontiersin.org/articles/10.3389/fenrg.2021.696785/full.

[11] V. Kashparov, S. Levchuk, M. Zhurba, V. Protsak, N. A. Beresford and J. S. Chaplow, "Spatial radionuclide deposition data from the 60 km radial area around the Chernobyl Nuclear Power Plant: results from a sampling survey in 1987", Earth System Science Data, vol. 12, no. 3, pp.1861-1875, 2020, https://doi.org/10.5194/essd-12-1861-2020.

[12] Z. Sun, C. Zhang, J. Chen, P. Tang and A. Yilmaz, "Predictive nuclear power plant outage control through computer vision and data-driven simulation", Progress in Nuclear Energy, vol. 127, no. 103448, pp. 1-11, september 2020, https://doi.org/10.1016/j.pnucene.2020.103448.

[13] H. Wang, M. Peng, R. Xu, A. Ayodeji and H. Xia, "Remaining Useful Life Prediction Based on Improved Temporal Convolutional Network for Nuclear Power Plant Valves, Frontiers in Energy Research, vol. 8, no. 584463, pp. 1-11, November 2020, https://doi.org/10.3389/fenrg.2020.584463.

[14] H. Arabi and H. Zaidi, "Applications of artificial intelligence and deep learning in molecular imaging and Radiotherapy", European Journal of Hybrid Imaging, vol. 4, no. 17, pp. 1-23, September 2020, https://doi.org/10.1186/s41824-020-00086-8.

[15] M. Gomez-Fernandez, W. K. Wong, A. Tokuhiro, K. Welter, A. M. Alhawsawi, H. Yang and K. Higley," Isotope identification using deep learning: An explanation", Nuclear Inst. and Methods in Physics Research- A, vol. 988, no. 164925, Feburary 2021, pp.1-7, https://doi.org/10.1016/j.nima.2020.164925.

[16] S.M. Galib, P.K. Bhowmik, A.V. Avachat, H.K. Lee," A comparative study of machine learning methods for automated identification of radioisotopes using NaI gamma-ray spectra", Nuclear Engineering and Technology, vol. 53, no. 2, pp. 4072-4079, December 2021, https://doi.org/10.1016/j.net.2021.06.020.

[17] J. M. Ghawaly, A. D. Nicholson, D. E. Peplow, C. M. Anderson-Cook, K. L. Myers, D. E. Archer, M. J. Willis and B. J. Quiter, "Data for training and testing radiation detection algorithms in an urban environment", Scientific Data, vol. 7, no. 328, pp. 1-6, October 2020, https://doi.org/10.1038/s41597-020-00672-2.

[18] K. Revathi, T. Tamilselvi, R. Arunkumar and T. Divya, "Spot Fire: An Intelligent Forest Fire Detection System Design With Machine Learning," 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS), Pudukkottai, India, pp. 532-537, 2022, doi: 10.1109/ICACRS55517.2022.10029044.

[19] T. Tamilselvi, D. Lakshmi, R. Lavanya and K. Revathi, "Digital Companion for Elders in Tracking Health and Intelligent Recommendation Support using Deep Learning", International Journal on Recent and Innovation Trends in Computing and Communication, vol. 11, no. 3, pp. 145-152, March 2023, https://doi.org/10.17762/ijritcc.v11i3.6331.

[20] A. G. Gad, "Particle Swarm Optimization Algorithm and Its Applications: A Systematic Review", Arch Computat Methods Eng, vol. 29, pp. 2531–2561, 2022, https://doi.org/10.1007/s11831-021-09694-4.

[21] Adrian Tam, "A Gentle Introduction to Particle Swarm Optimization", Machine Learning Matery, September 2021, https://machinelearningmastery.com/a-gentle-introduction-to-particle-swarm-optimization/.