Predicting and Monitoring Radiation Exposure of Radiographers Using Fuzzy Preprocessing and Deep Learning

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Abstract: This study introduces an AI-driven approach to enhance radiation exposure monitoring for radiographers, addressing the limitations of traditional personal dosimeters. These dosimeters provide passive feedback, uncertain measurements, and lack real-time or predictive capabilities. To overcome this, fuzzy logic and deep learning are integrated. Fuzzy logic categorizes continuous variables—such as radiation dose, time spent, and distance from the source—into low, medium, and high-risk levels. Deep learning is then used to predict radiation exposure and classify these risk categories. The model achieves 98% accuracy, closely matching traditional dosimeter results while significantly improving precision and recall, outperforming the model with deep learning only. This makes radiation exposure classification more reliable. By transforming continuous data into clear, interpretable risk categories, actionable safety insights are provided to guide decision-making. Furthermore, this AI-based system shifts radiation dose management from a reactive to a proactive approach, enabling real-time monitoring and reducing reliance on dosimeters.

Keywords: Radiation Exposure, Radiographers, Dosimetry, Fuzzy Preprocessing, Fuzzy Categorization, Fuzzy Deep Learning (FDL).

1. INTRODUCTION

The healthcare industry is increasingly focused on optimizing radiographer radiation exposure to ensure both patient safety and the well-being of medical professionals. Traditionally, the absorbed radiation dose experienced by radiographers is measured using personal dosimeters. However, this method has inherent limitations, such as long measurement periods, uncertainty and imprecision associated with measurements or subjective assessments. and the risk of loss or malfunction of these instruments (Abuzaid et al., 2024; Eaton et al., 2011). Such challenges can lead to gaps in data collection and may hinder the effective monitoring of radiation exposure.

To address these issues, this study investigates the potential of artificial intelligence (AI) as a complementary solution for assessing radiation exposure among Utilizing a comprehensive dataset that encompasses demographic information, exam types, and radiation dose measurements, it was aimed to classify cumulative radiation doses into three categories: low, medium, and high.

In this paper, a hybrid approach was proposed that integrates fuzzy logic and deep learning to significantly improve radiation exposure classification (Abdalla et al., 2024). Fuzzy logic was used to discretize continuous variables like average radiation dose, exposure duration, and distance into interpretable risk categories (low, medium, and high). This preprocessing step transformed raw data into a format more suitable for the deep learning model, enhancing its input quality. The categorized data served as a robust foundation for the neural network, enabling it to effectively learn and capture complex patterns within the dataset.

The deep learning model, trained on the fuzzy-processed data, achieved exceptional results, including an accuracy of 98%, surpassing traditional methods. Recall scores improved across all dose categories, addressing challenges in distinguishing high radiation exposures. The integration of fuzzy logic not only enhanced the interpretability of the inputs but also strengthened the model's performance by effectively handling continuous and uncertain data. This combination demonstrated its ability to classify radiation exposure levels more effectively, offering a robust, reliable solution for proactive radiation safety management.

The findings underscore the effectiveness of fuzzy-based deep learning in predicting cumulative radiation doses among radiographers. By integrating AI into the assessment process, a more robust solution is aimed to be provided that addresses the limitations of traditional dosimetry methods. The subsequent sections will detail the methodology, experiments, results, and implications of the findings, offering valuable insights into the role of AI in managing radiation exposure in radiography.

The remainder of this paper is organized as follows: Section 2 presents a comprehensive literature review of existing approaches to radiographer radiation monitoring and the role of AI in healthcare. Section 3 details the methods used in this study, including data preprocessing, feature selection, and the development of both logistic regression and deep learning models. Section 4 describes the experimental setup, reports the results, and provides an in-depth discussion of model performance across dose categories. Finally, Section 5 concludes the paper, summarizing key findings and offering perspectives on future advancements in AI-driven radiation exposure management.

2. RELATED WORK

The integration of artificial intelligence (AI) in healthcare has garnered significant attention in recent years, particularly in enhancing patient safety and optimizing operational workflows (Sadeghi et al., 2024; Athota et al., 2020). AI's capability to analyze vast datasets and identify complex patterns presents transformative opportunities for improving clinical decision-making, diagnostic accuracy, and overall patient care (Jiang et al., 2017; Sukanya et al., 2022).

Numerous studies underscore the efficacy of AI across various healthcare applications. For example, machine learning algorithms have been employed to predict patient outcomes, streamline diagnostic processes, and personalize treatment plans (Noorbakhsh-Sabet et al., 2019; De Fauw et al., 2018). In radiology specifically, AI technologies, such as convolutional neural networks (CNNs), have demonstrated remarkable success in analyzing medical images (Esteva et al., 2017; Gulshan et al., 2016). These advanced algorithms assist radiologists in detecting anomalies, thereby reducing diagnostic errors and improving patient outcomes. Indeed, One approach to predicting dose distributions is to use convolutional neural networks (CNNs) that receive a 2D or 3D input in the form of planning computed tomography (CT) with organ-at-risk or planning target volume masks and produce a voxel-level dose distribution as its output (Rani et al., 2023; Dong et al., 2024).

In the context of radiation safety, AI has the potential to revolutionize the monitoring and management of occupational exposure (Bang et al., 2020; Fiagbedzi et al., 2022). Traditional methods, which rely on personal dosimeters, often provide retrospective data and are limited by their inability to offer real-time insights (Gulec and McGoron, 2022) . While conventional equipment is essential for measuring radiation exposure, it can result in gaps in safety monitoring due to delays in data collection and the risk of equipment failure.

Mentzel et al. have developed a model that can accurately predict the date of exposure from thermoluminescence dosimeter data (Jhanwar et al., 2022). Furthermore, deep learning can also be used to analyze radiation exposure data to identify trends and patterns (Mentzel et al., 2021).

By analyzing radiation exposure data, radiation protection officers can identify areas where radiation exposure can be reduced, and take steps to improve patient and staff safety.

Deep learning has the potential to revolutionize the field of radiation therapy by improving the accuracy of dose monitoring and prediction, and enabling the analysis of radiation exposure data (Chang et al., 2014). This study aims to contribute to the existing body of knowledge by exploring the application of AI in radiation dose management for radiographers. By leveraging advanced AI techniques, the safety of radiographers is enhanced through predictive modeling that complements and extends the capabilities of conventional equipment. This approach not only fosters a safer environment for radiographers but also promotes a more efficient workflow in radiology departments, ultimately ensuring compliance with safety standards and enhancing overall healthcare quality.

3. METHODOLOGY

This study employed a hybrid research design combining fuzzy logic and deep learning methodologies to predict radiation risk levels accurately (See Fig. 1). The objective was to address the complexity and inherent uncertainty in radiation exposure data by leveraging the interpretability of fuzzy logic and the predictive power of deep learning.

The approach involved preprocessing raw radiation data, applying fuzzy logic for risk categorization, and training a neural network to classify exposure levels. This hybrid model was designed to enhance both the interpretability of predictions and their overall accuracy, making it particularly suitable for healthcare applications.

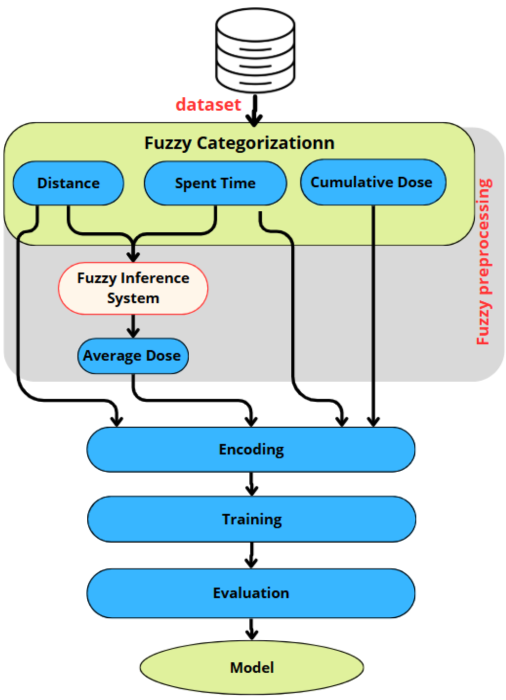

Figure 1. Proposed approach flowchart

3.1 Dataset description

The dataset employed in this study contains a range of features pertinent to radiographer radiation exposure, including demographic information, exam types, and radiation dose measurements. Key features include (see Table 1):

Table 1. Features of Radiographer Radiation Exposure Data

Feature	Description
Radiographer ID	Unique ID for each radiographer
Date	Exam date
Number of Exams	Total exams performed
Type of Exam	Category (X-ray, CT)
Average Dose (mGy)	Avg. radiation dose per exam
Time Spent (minutes)	Duration per exam
Distance from Source (m)	Distance from radiation source
Protective Equipment Used	Type of protective gear
Experience (years)	Radiographer experience
Patient Size (kg)	Patient weight
Equipment Type	Type of equipment used
Procedure Type	Specific procedure performed
Cumulative Dose (mGy)	Total radiation dose for radiographer

3.2 Fuzzy Preprocessing

Data preprocessing was an essential step to ensure the dataset's compatibility with the model and to enhance its overall performance (Timcenko and Gajin, 2021). Initially, missing values were addressed using median imputation, which effectively filled gaps in the data while minimizing potential biases. Continuous variables were normalized to a [0,1] range to ensure uniformity and improve the model's efficiency during training. For categorical data, one-hot encoding was applied to convert non-numeric variables into a format compatible with the neural network. Additionally, fuzzy logic was employed to enhance interpretability by transforming continuous features into linguistic categories, such as "low," "medium," and "high," enabling a more nuanced representation of data and addressing inherent uncertainties. Table 2 summarizes the transformations applied to each feature:

Table 2. Features and Transformations

Feature	Transformation
Time Spent (minutes)	Fuzzy (Short, Medium, Long)
Distance from Source (m)	Fuzzy (Near, Moderate, Far)
Average Dose (mGy)	Fuzzy (Levels 0–1)
Cumulative Dose (mGy)	Fuzzy (Low, Medium, High)

Fuzzy Logic-Based Categorization.

To manage uncertainty in continuous data, fuzzy logic was employed by applying membership functions tailored to each feature based on clinical thresholds (Birou et al., 2010; Al-gizi et al., 2017). For the Cumulative Dose (mGy), three categories were defined: Low, Medium and High. For Time Spent (minutes), the categories were Short (trapezoidal function for less than 10 minutes), Medium (triangular function centered at 15 minutes), and Long (trapezoidal function for more than 30 minutes). Finally, for Distance from Source (m), the categories were Near (trapezoidal function for less than 1 m), Moderate (triangular function centered at 2 m), and Far (trapezoidal function for greater than 3 m). This approach effectively models the uncertainty associated with these continuous variables, enabling more flexible decision-making in clinical settings. Fuzzy membership scores were generated for each category, providing an interpretable basis for risk classification. The visualization is shown below (See Fig.2, 3, and 4).

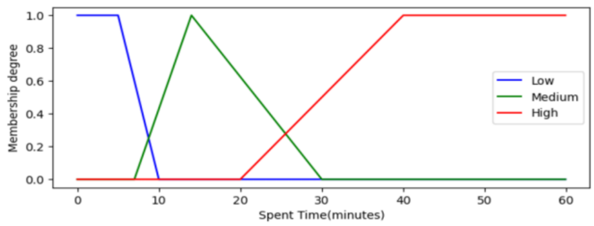

Figure 2. Memberships functions for Time spent categorization

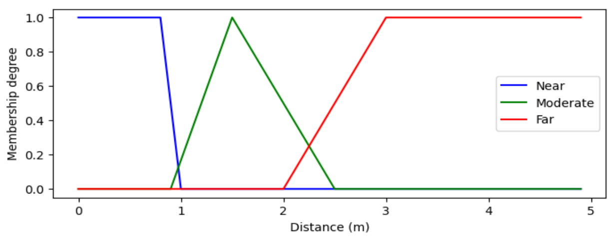

Figure 3. Memberships functions for Distance categorization

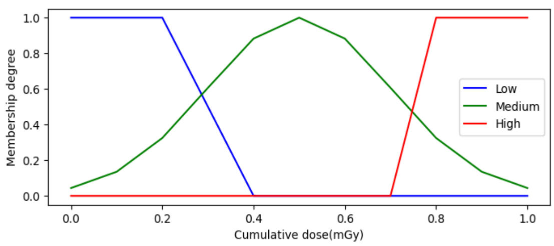

Figure 4. Memberships functions for Cumulative dose categorization

The original numerical features, Distance and Time, are replaced with the corresponding membership degrees of their fuzzy sets. These fuzzy sets, represented by linguistic variables like "Near," "Medium," and "Far" for distance, and "Short," "Medium," and "High" for time, allow for a more nuanced representation of uncertainty and imprecision in the data. For instance; Spent Time is replaced with the features Time_Low, Time_Medium and Time_High).

Fuzzy inference system for average dose

There exists a correlation between datasets features where average dose can be deduced from Time Spent and distance.

In the proposed approach, aiming to reduce uncertainties and misleading measurements, a fuzzy inference system has been designed to infer the average dose using experts' rules. The fuzzy inference system scheme is depicted in Fig. 5.

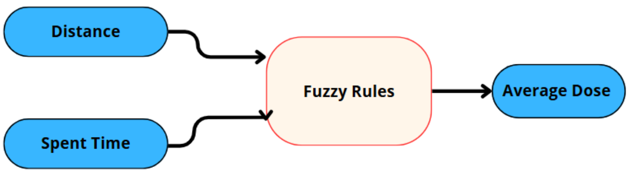

Figure 5. Fuzzy inference system for average dose

The inputs for this inference system, time and distance, were characterized using fuzzy membership functions, as illustrated. The output variable, average dose, was similarly represented by a fuzzy membership function, as depicted in Fig. 6.

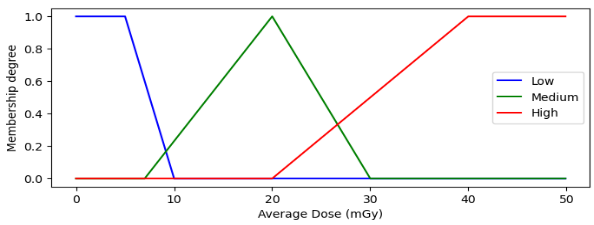

Figure 6. Memberships functions for average dose(inference system output)

The fuzzy rules are designed to establish relationships between the input variables (Time Spent, and Distance from Source), and the target category of Average Dose (Low, Medium, High) based on expert knowledge and clinical guidelines. The obtained rules are represented in Table 3.

Table3. Fuzzy rules for average dose inference

		Time		
		Short	Medium	Long
Distance	Near	Medium	High	High
	Moderate	Low	High	Medium
	Far	Low	Medium	Medium

3.3 Deep Learning Model Design

A neural network was designed to integrate the fuzzy logic outputs and refine the model's predictions (Salehi and Mirzakuchaki, 2022). The architecture consisted of several key components: the input layer, which received the fuzzy-transformed features as inputs, ensuring that the data was in an interpretable format.

The network included two hidden layers, each containing 64 neurons, and utilized the ReLU activation function to capture and model non-linear patterns within the data. Finally, the output layer featured a softmax function with three neurons, each corresponding to one of the risk levels—low, medium, or high—allowing the model to classify radiation exposure risks effectively. This architecture enabled the model to leverage both fuzzy logic and deep learning, providing a robust and interpretable solution for risk prediction. The model was compiled with the Adam optimizer for adaptive learning and sparse categorical crossentropy as the loss function. Table 4 outlines the model architecture:

Table 4. Neural Network Architecture Details

Layer	Type	# of Neurons	Act. Function
Input Layer	Dense	15 (input features)	-
Hidden Layer 1	Dense	64	ReLU
Hidden Layer 2	Dense	64	ReLU
Output Layer	Dense	3	Softmax

3.4 Training and Validation

To ensure robust evaluation, the dataset was split into training and testing subsets, and to evaluate the performance of the predictive model, several key metrics were employed. First, the accuracy of the model was assessed to determine the overall proportion of correct predictions made across all classes. The confusion matrix was also used to provide a more detailed view of the model's performance by showing the true positive, true negative, false positive, and false negative predictions for each risk level (Low, Medium, High). In addition, the classification report was generated, offering a comprehensive evaluation of precision, recall, and F1-score for each class, which helped assess the model's ability to correctly classify each category (Sidaoui and Sadouni, 2023; Altuncu et al., 2021). The ROC-AUC score was computed to evaluate the model's ability to distinguish between the classes, where a higher score indicates better discriminatory performance. The ROC curves could also visualize the trade-offs between the true positive rate and false positive rate for each class, providing further insight into the model's performance across different thresholds (Bahaweres and Nuraini, 2024). These metrics were crucial for ensuring the robustness and reliability of the model's predictions.

3.5 Algorithm for Radiation Dose Classification Using Fuzzy Logic and Deep Learning

The following algorithm outlines our approach for classifying radiation doses using fuzzy logic in conjunction with deep learning. It begins with preprocessing the dataset, where fuzzy membership functions are applied to categorize the radiation exposure into Low, Medium, and High doses. The dataset is then split into training and testing sets, and a deep learning model is trained to predict these categories. The new approach incorporates fuzzy logic to handle continuous input values for dose, time, and distance, providing a more flexible classification system. The global approach is represented in Algorithm 1.

ALGORITHM 1: RADIATION DOSE CLASSIFICATION USING FUZZY LOGIC AND DEEP LEARNING

Input: *Dataset*
Output: *Trained model*
Initialization
Load the dataset.
Dataset =fuzzy_preprocessing(dataset)//Algorithm 2
Split the dataset into training and testing sets: X_train, X_test, y_train, y_test.
Deep learning model setting
Train the model on the training data (X_train, y_train).
Validate the model on the testing data (`X_test`, `y_test`)
Make predictions on the test data (`X_test`).
Evaluate the obtained model with F1-score

The fuzzy preprocessing proposed in this paper is detailed in Algorithm 2

ALGORITHM 2: FUZZY PREPROCESSING

Input: D1: original dataset
Output: D2: preprocessed dataset
COL= features(D1)
NF=Numerical features// Time and Distance
F={} //preprocessed features
for each f_i in NF
    cat_1, cat_2…. cat_n =Fuzzy(f_i)// Define fuzzy membership functions for f_i
    COL=COL+ {cat_1, cat_2…. cat_n }//add cat_1, cat_2…. cat_n as new features
    F=F+{fi}
    for each sample j in D1
        μ_1, μ_2. ..μ_n =Fuzzify(f_{ij})// get membership degrees for values j of feature i
        D1[[cat_1, cat_2…. cat_n], j]= [μ_1, μ_1 , … μ,] //update new added features values
    end for
end for
cat_1, cat_2…. cat_n =Fuzzy(AverageDose)// Define fuzzy membership functions for AverageDose
for each sample j in D1
    μ_1, μ_1 … μ_n =FuzzyRules(D1[Time, j], D1[Distance, j])// Apply fuzzy rules
    D1[AverageDose, j]=cat(max(μ_1, μ_1 , … μ_n))
end for
cat_1, cat_2…. cat_n =Fuzzy(target)// fuzzy membership functions for target
for each sample j in D1
    μ_1, μ_1 … μ_n =Fuzzify(D1[target, j])// get membership degrees for values j of feature i
    D1[target, j] =cat(max(μ_1, μ_1 , … μ_n))// category of the max membership degree
end for
D2=D1-F
D2=encoding(D2)
Return D2

4. EXPERIMENT, RESULTS, AND DISCUSSION

In this experiment, The performance of a deep learning model designed for classifying radiation exposure levels into three categories: low, medium, and high doses was evaluated. The dataset was preprocessed using fuzzy logic transformations, taking into account continuous variables like radiation dose and exposure time. The model was trained using 80% of the dataset. Key parameters were carefully selected to optimize the training process, as outlined in Table 5. A batch size of 32 was chosen to enhance the efficiency of gradient updates, while 50 epochs were set to allow for sufficient training without overfitting. Performance was monitored using a validation set to assess the model’s progress after each epoch. Regularization techniques, including dropout layers and early stopping, were initially explored to mitigate the risk of overfitting (Salehi and Mirzakuchaki, 2022). However, after fine-tuning, dropout layers were excluded from the final model due to the stability achieved during training, ensuring optimal performance without unnecessary complexity.

Table 5. Key Training Parameters

Parameter	Value	Description
Batch Size	32	Optimizes gradient updates
Epochs	50	Prevents overfitting
Validation Set	20%	Assesses performance during training
Regularization	Dropout	Mitigates overfitting

This approach ensured that the model was trained effectively while avoiding overfitting, leading to robust and reliable performance on the testing dataset

4.1 Confusion Matrix

The confusion matrix in Table 6 shows the classification results for each radiation exposure category. It compares the model's predictions against the true labels, demonstrating its effectiveness in accurately classifying the majority of instances across all three exposure categories, Low, Medium, and High.

To further illustrate the model's performance, Fig. 7 presents the model’s accuracy over the training epochs. As shown in the figure, the model’s accuracy steadily improves during the training phase, reaching a high level of accuracy by the end of the training process. This indicates that the model is effectively learning and generalizing from the data.

On the other hand, Fig. 8 depicts the model’s loss over the same epochs. The plot shows a significant reduction in loss during the early stages of training, followed by a stabilization phase (Ran and Cai, 2024; Rani et al., 2023). This suggests that the model quickly adapts to the training data and achieves a low loss, indicating a strong fit to the training set. However, the small fluctuations observed in the test loss towards the later epochs indicate that the model may experience some minor overfitting, though its overall performance remains robust.

Together, the confusion matrix and the figures provide a comprehensive overview of the model's classification ability, highlighting its accuracy, generalization capacity, and stability across various training conditions.

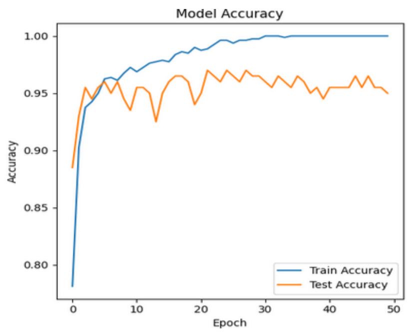

Figure 7. Model Accuracy over Epochs

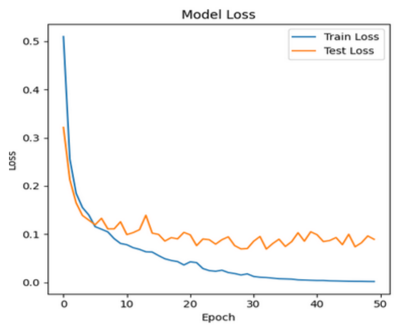

Figure8. Model Loss over Epochs

Table 6. Confusion Matrix for Radiation Dose Classification

True / Predicted	Low (0)	Medium (1)	High (2)
Low (0)	19	0	0
Medium (1)	0	160	0
High (2)	2	3	16

4.2 Performance Metrics

The detailed metrics for model performance are as follows (Table 7), which summarize the precision, recall, and F1-score for each class of radiation exposure level (Low, Medium, High). The model shows high precision and recall values across the three classes, with the Low and Medium categories achieving perfect recall of 1.00, which indicates that the model correctly identified all instances in these classes. However, the High category shows a decrease in recall (0.76), suggesting that while the model's precision remains high (1.00), it has a relatively lower capacity to correctly identify all instances of high exposure.

These results show the model's strong performance overall, with an accuracy of 0.97 and macro and weighted averages indicating consistently good results across all categories. The high precision and F1-scores suggest that the model is quite effective in minimizing both false positives and false negatives, particularly for Low and Medium categories.

Table 7. Deep Learning Results

Class	Precision	Recall	F1-Score	Support
Low (0)	0.90	1.00	0.95	19
Medium (1)	0.98	1.00	0.99	160
High (2)	1.00	0.76	0.86	21
Accuracy			0.97	200
Macro Avg	0.96	0.92	0.94	200
Weighted Avg	0.98	0.97	0.97	200

Additionally, the ROC-AUC score achieved was 0.998, demonstrating the model's excellent ability to distinguish between the three radiation exposure levels. This metric further highlights the model's robustness in classification tasks, as a high ROC-AUC score indicates a low false positive rate and a high true positive rate across the different classes.

The Precision, Recall, and F1-Score for each class are visually summarized in Fig. 9, which provides a clear and accessible representation of the model's performance across the three classes. The bar chart in the figure compares the scores for each class—Low, Medium, and High—showing that while the model excels in the Low and Medium categories, there is a noticeable dip in performance for the High category, where recall is somewhat lower than expected. This chart serves to illustrate the model's strengths and weaknesses in a concise manner, making it easier to interpret the metrics and understand the areas for potential improvement.

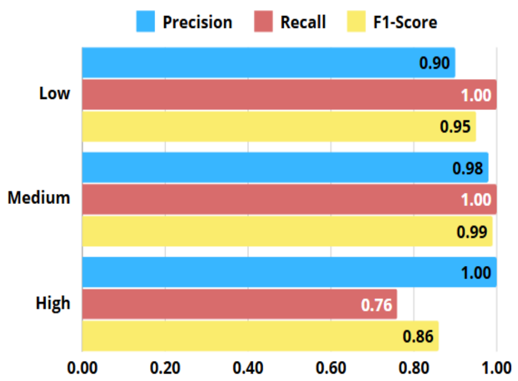

Figure 9. Classification Metrics for each Class

4.3. Model Performance and comparison

The results, as illustrated in Fig. 10, highlight the performance gap between the Fuzzy Deep Learning (FDL) and standard Deep Learning (DL) approaches for low-dose classification. The DL model achieves a precision of 0.44, recall of 0.79, and an F1-score of 0.57. In contrast, the FDL model significantly improves these metrics, achieving precision, recall, and F1-scores of 0.90, 1.00, and 0.95, respectively. This improvement demonstrates the FDL approach's ability to minimize false positives and detect all low-dose cases, leveraging fuzzy logic to handle overlapping and ambiguous data points effectively.

As depicted in Fig. 11, for medium-dose classification, the DL model performs relatively well, with precision of 0.95, recall of 0.97, and an F1-score of 0.96. However, the FDL model surpasses these results with precision of 0.98, recall of 1.00, and an F1-score of 0.99. The integration of fuzzy logic enhances the model’s ability to establish more precise decision boundaries, reducing false negatives and ensuring comprehensive detection of medium-dose cases. These results emphasize the incremental benefit of adding fuzzy logic to a deep learning framework.

Finally, Fig. 12 reveals the most substantial improvement in high-dose classification. The DL model struggles with recall, achieving only 0.76, resulting in an F1-score of 0.86 despite a precision of 1.00. This indicates the DL model misclassifies some high-dose cases as medium doses. Conversely, the FDL model achieves perfect precision and recall of 1.00, with an F1-score of 0.95, effectively resolving this challenge. These results underscore the FDL approach's ability to handle uncertainty and improve classification accuracy across all dose categories, demonstrating its value for real-world applications in radiation monitoring.

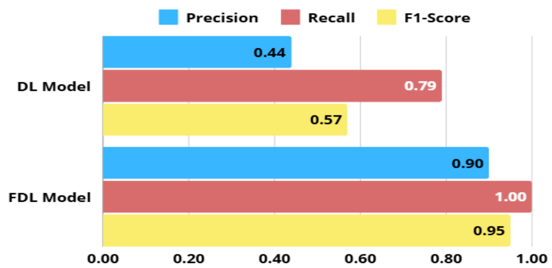

Figure 10. Low Class Metrics for DL Model and Fuzzy DL Model

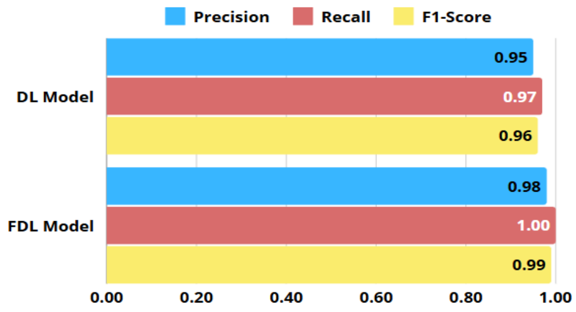

Figure 11. Medium Class Metrics for DL Model and Fuzzy DL Model

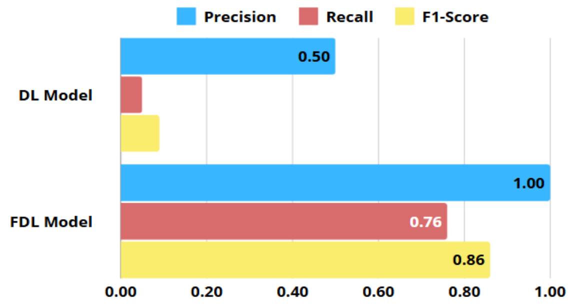

Figure 12. High Class Metrics for DL Model and Fuzzy DL Model

4.4 Discussion

The fuzzy deep learning (FDL) approach significantly outperforms the standard deep learning (DL) model in classifying radiation exposure levels, achieving perfect recall (1.00) for both low and medium doses and a much higher recall of 0.95 for high doses compared to the DL model’s recall of 0.76 for high doses. This improvement highlights the FDL model's superior ability to distinguish between medium and high radiation doses, addressing a critical limitation of the DL model. Additionally, the FDL model excels in minimizing false positives, with precision values of 0.98 for medium doses and 1.00 for high doses. Its F1-scores also reflect its robustness, with 0.99 for medium doses and 0.95 for high doses, reinforcing its reliability and effectiveness across different exposure levels.

The integration of fuzzy logic in the FDL model is key to its improved performance. Fuzzy logic allows the model to better handle uncertainties and overlapping features in the data, providing a nuanced understanding of the subtle distinctions between radiation exposure levels. By introducing degrees of membership, fuzzy logic enhances the model's interpretability and flexibility, enabling it to classify radiation doses more effectively than a standard DL model. This is particularly valuable in real-world applications, where understanding the reasoning behind classifications can lead to more informed decisions regarding worker safety, radiation therapy, and emergency response strategies.

When comparing the FDL model to traditional personnel dosimeters, the advantages become evident. Personnel dosimeters, which require physical placement on the body and manual data collection, are prone to human error and are time-consuming. Furthermore, the process of analyzing radiation exposure manually introduces inconsistencies and delays. In contrast, the FDL model can automate the classification process, offering fast, real-time predictions with minimal human intervention. This not only improves the efficiency of radiation exposure monitoring but also makes it scalable, enabling large-scale monitoring across different settings, such as hospitals, industrial sites, or environmental monitoring stations. The ability to assess radiation exposure continuously and in real time could significantly improve occupational safety and healthcare outcomes.

Despite the FDL model's strong performance, there is still potential for improvement. The high-dose recall of 0.95, while impressive, suggests that there are still some subtle distinctions between high and medium doses that the model could better capture. Future work could focus on refining the model's architecture, such as exploring data augmentation techniques, transfer learning, or more sophisticated feature extraction methods. Moreover, incorporating environmental variables—such as shielding effects, geographic factors, or the type of radiation exposure—could further enhance the model's robustness and its ability to generalize across different scenarios. Expanding the dataset to include more diverse conditions and real-world scenarios will help ensure that the model continues to perform effectively in varied operational environments.

5. CONCLUSION

In conclusion, this study highlights the critical need for enhanced radiation dose monitoring in radiology, particularly for radiographers. By incorporating AI-driven techniques, it has been demonstrated that these methods can effectively complement traditional physical instruments, such as personal dosimeters, in predicting and monitoring cumulative radiation exposure. The deep learning model achieved a remarkable accuracy of 97% in classifying radiation doses, illustrating the potential of AI to offer precise and real-time monitoring capabilities. This approach enhances the predictive accuracy of radiation exposure, offering a more efficient tool to work alongside conventional measurement devices, thereby reducing reliance on physical instruments and optimizing radiation safety.

Future research will delve deeper into the potential of fuzzy logic by categorizing additional relevant features, such as patient size, to further enhance the model's predictive capabilities. Furthermore, the integration of advanced AI techniques, including ensemble learning and more complex neural network architectures, is aimed at improving the model's accuracy, robustness, and generalizability. By expanding the scope to encompass diverse datasets, imaging modalities, and patient demographics, the goal is to develop a comprehensive and versatile AI solution that can seamlessly complement existing physics-based tools. This will not only strengthen radiation dose management but also contribute to optimizing safety protocols, improving operational efficiency, and supporting radiographers' well-being. Ultimately, this research paves the way for a more proactive, data-driven approach to radiation dose monitoring, enhancing both safety and quality of care in radiology departments.

REFERENCES

Abdalla, A. Y., Abdalla, T. Y., and Chyaid, A. M. (2024), "Internet of Things-Based Fuzzy Systems for Medical Applications: A Review," IEEE Access, vol. 12, pp. 163883–163902, doi:10.1109/ACCESS.2024.3487812.

Abuzaid, M, Noorajan, Z, Elshami, W, and Ibham, M (2024), "Monitoring Occupational Radiation Dose in Radiography Students: Implications for Safety and Training," Safety, vol. 10, no. 2, p. 35, doi:10.3390/safety10020035

Al-gizi, A., Al-chlaihawi, S., Louzazni, M., and Craciunescu, A. (2017), "Genetically Optimization of an Asymmetrical Fuzzy Logic

Based Photovoltaic Maximum Power Point Tracking Controller," Advances in Electrical and Computer Engineering, vol. 17, no. 4, pp. 69–76, doi:10.4316/AECE.2017.04009.

Altuncu, M. A., Gulagiz, F. K., Ozcan, H., Bayir, O. F., Gezgin, A., Niyazov, A., Cavuslu, M. A., Sahin, S. (2021), "Deep Learning Based DNS Tunneling Detection and Blocking System," Advances in Electrical and Computer Engineering, vol. 21, no. 3, pp. 39–48, doi:10.4316/AECE.2021.03005.

Athota, L., Shukla, V. K., Pandey, N., and Rana, A. (2020), "Chatbot for Healthcare System Using Artificial Intelligence," 2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), Noida, India, pp. 619–622, doi:10.1109/ICRITO48877.2020.9197833.

Bahaweres, R. B., and Nuraini, I. K. (2024), "Cost-sensitive Approach for Improving AUC-ROC Curve of Software Defect Prediction," 2024 International Seminar on Intelligent Technology and Its Applications (ISITIA), Mataram, Indonesia, pp. 178–183, doi:10.1109/ISITIA63062.2024.10668184.

Bai, X., Zhou, Z., Luo, Y., Yang, H., Zhu, H., Chen, S., and Pan, H. (2022), "Development and Evaluation of a Machine Learning Prediction Model for Small-for-Gestational-Age Births in Women Exposed to Radiation before Pregnancy," Journal of Personalized Medicine, vol. 12, no. 4, p. 550, doi:10.3390/jpm12040550.

Bang, J. Y., Hough, M., Hawes, R. H., and Varadarajulu, S. (2020), "Use of Artificial Intelligence to Reduce Radiation Exposure at Fluoroscopy-Guided Endoscopic Procedures," American Journal of Gastroenterology, vol. 115, no. 4, pp. 555–561, doi:10.14309/ajg.0000000000000565.

Birou, I., Maier, V., Pavel, S., and Rusu, C. (2010), "Indirect Vector Control of an Induction Motor with Fuzzy-Logic based Speed Controller," Advances in Electrical and Computer Engineering, vol. 10, no. 1, pp. 116–120, doi:10.4316/AECE.2010.01021.

Chang, Y., Kim, Ah na, Oh, I., Woo, N., Kim, Hae-Kyoung, and Kim, Jae Hun (2014), "The Radiation Exposure of Radiographer Related to the Location in C-arm Fluoroscopy-guided Pain Interventions," The Korean Journal of Pain.

Currie, G. M., and Rohren, E. M. (2023), "Radiation Dosimetry, Artificial Intelligence and Digital Twins: Old Dog, New Tricks," Seminars in Nuclear Medicine, vol. 53, no. 3, pp. 457–466, doi:10.1053/j.semnuclmed.2022.10.007.

De Fauw, J., et al. (2018), "Clinically applicable deep learning for diagnosis and referral in retinal disease," Nature Medicine, vol. 24, no. 9, pp. 1342–1350, doi:10.1038/s41591-018-0107-6.

Dong, Z., Chen, Y., Gay, H., Hao, Y., Hugo, G., and Samson, P. (2024), "Large-Language-Model Empowered Dose Volume Histogram Prediction for Intensity Modulated Radiotherapy," arXiv.org.

Eaton, D. J., Gonzalez, R., Duck, S., and Keshtgar, M. (2011), "Radiation protection for an intra-operative X-ray device," British Journal of Radiology, vol. 84, no. 1007, pp. 1034–1039, doi:10.1259/bjr/29466902.

Esteva, A., Kuprel, B., Novoa, R., et al. (2017), "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, pp. 115–118, doi:10.1038/nature21056.

Fiagbedzi, E., Gorleku, P., Nyarko, S., Atuwo-Ampoh, V., Fiagan, Y., and Asare, A. (2022), "The Role of Artificial Intelligence (AI) in Radiation Protection of Computed Tomography and Fluoroscopy: A Review," Open Journal of Medical Imaging, vol. 12, pp. 25–36, doi:10.4236/ojmi.2022.121004.

Gulec, S. A., and McGoron, A. J. (2022), "Radiomicrosphere Dosimetry: Principles and Current State of the Art," Seminars in Nuclear Medicine, vol. 52, no. 2, pp. 215–228, doi:10.1053/j.semnuclmed.2021.12.009.

Gulshan, V., Peng, L., Coram, M., et al. (2016), "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs," JAMA, vol. 316, no. 22, pp. 2402–2410, doi:10.1001/jama.2016.17216.

Jhanwar, G., Dahiya, N., Ghahremani, P., Zarepisheh, M., and Nadeem, S. (2022), "Domain Knowledge Driven 3D Dose Prediction Using Moment-Based Loss Function," Physics in Medicine and Biology.

Jiang, F., et al. (2017), "Artificial intelligence in healthcare: Past, present and future," Stroke and Vascular Neurology, vol. 2, no. 4, doi:10.1136/svn-2017-000101.

Kassar, M., Drobnjakovic, M., Birindelli, G., Xue, S., Gafita, A., Wendler, T., Afshar-Oromieh, A., Navab, N., Weber, W. A., Eiber, M., Ziegler, S., Rominger, A., and Shi, K. (2024), "PBPK-Adapted Deep Learning for Pretherapy Prediction of Voxelwise Dosimetry: In-Silico Proof of Concept," IEEE Transactions on Radiation and Plasma Medical Sciences, vol. 8, no. 6, pp. 646–654, doi:10.1109/TRPMS.2024.3381849.

Liu, M., Nagpal, C., and Dubrawski, A. (2024), "Deep Survival Models Can Improve Long-Term Mortality Risk Estimates from Chest Radiographs," Forecasting.

Mentzel, F., Derugin, E., Jansen, H., Kröninger, K., Nackenhorst, O., Walbersloh, J., et al. (2021), "No More Glowing in the Dark: How Deep Learning Improves Exposure Date Estimation in Thermoluminescence Dosimetry," Journal of Radiological Protection.

Noorbakhsh-Sabet, N., Zand, R., Zhang, Y., and Abedi, V. (2019), "Artificial Intelligence Transforms the Future of Health Care," American Journal of Medicine, vol. 132, no. 7, pp. 795–801, doi:10.1016/j.amjmed.2019.01.017.

Ran, L., and Cai, C. (2024), "Topo-Loss: A Novel Loss Function for Learning Multiple Manifold Structures in Image Classification with Deep Neural Networks," 2024 5th International Conference on Computer Vision, Image and Deep Learning, Zhuhai, China, pp. 703–707, doi:10.1109/CVIDL62147.2024.10604103.

Rani, G., Dhaka, V. S., Vocaturo, E., and Zumpano, E. (2023), "Crop Loss Estimation in Maize Agriculture: A Deep Learning Perspective," 2023 IEEE International Conference on Big Data (BigData), Sorrento, Italy, pp. 3499–3502, doi:10.1109/BigData59044.2023.10386301

Sadeghi, Z., Alizadehsani, R., Cifci, M. A., Kausar, S., Rehman, R., Mahanta, P., Bora, P. K., Almasri, A., Alkhawaldeh, R. S., Hussain, S., Alatas, B., Shoeibi, A., Moosaei, H., Hladík, M., Nahavandi, S., and Pardalos, P. M. (2024), "A review of Explainable Artificial Intelligence in healthcare," Computers and Electrical Engineering, vol. 118, no. A, p. 109370, doi:10.1016/j.compeleceng.2024.109370.

Salehi, M., and Mirzakuchaki, S. (2022), "A Novel Approach to Speech Enhancement Based on Deep Neural Networks," Advances in Electrical and Computer Engineering, vol. 22, no. 2, pp. 71–78, doi:10.4316/AECE.2022.02009.

Shukla, V. K., Pandey, N., and Rana, A. (2020), "Chatbot for Healthcare System Using Artificial Intelligence," 2020 8th International Conference on Reliability, Infocom Technologies and Optimization), Noida, India, pp.619–622

Sidaoui, B., and Sadouni, K. (2023), "Epilepsy Seizure Prediction from EEG Signal Using Machine Learning Techniques," Advances in Electrical and Computer Engineering, vol. 23, no. 2, pp. 47–54, doi:10.4316/AECE.2023.02006.

Sukanya, J., Gandhi, K. R., and Palanisamy, V. (2022), "An assessment of machine learning algorithms for healthcare analysis based on improved MapReduce," Advances in Engineering Software, vol. 173, p. 103285, doi:10.1016/j.advengsoft.2022.103285.

Timcenko, V., and Gajin, S. (2021), "Machine Learning Enhanced Entropy-Based Network Anomaly Detection," Advances in Electrical and Computer Engineering, vol. 21, no. 4, pp. 51–60, doi:10.4316/AECE.2021.04006.

Zadeh, L. A. (1965), "Fuzzy Sets," Information and Control, vol. 8, no. 3, pp. 338–353, doi:10.1016/S0019-9958(65)90241-X.