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ORIGINAL ARTICLE

Prediction of Radiation-Induced Abnormality in Liver Enzymes from Machine Learning (ML) Algorithms

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ABSTRACT

Background: Exposure to ionizing radiation from medical radiation equipment during cancer diagnosis and treatment can alter the biochemistry of hospital personnel by triggering the oxidative stress process.
Aim: To develop a Simple-Linear-Regression algorithm with supervised learning applied to find the correlation between liver enzymes with the AAED (mSv) in low-dose medical radiation workers.
Methodology: Radiology & Nuclear Medicine Radiation workers from INMOLHospital were included. The AAED (annual average effective radiation doses) received from TLDs were measured by Radiation Dosimetry Laboratory. The models were trained and applied to the sample data set.
Results: The mean value of AAED was 0.28 mSv. Half of the workers were found with high ALT levels and around 20% were found with altered AST levels. The models were also successfully cross-validated. ALT (R^2= 0.025) & AST (R^2= 0.00072) were having very weak relationships with AAED. From regression equations, it is inferred that for every unit increase in AAED (mSv), there will be a 12.98 unit decrease in ALT (U/L) and a 0.63 unit increase in AST (U/L) values.
Conclusion: Our ML model was successfully implemented to predict the alteration or abnormality in the liver enzymes from radiation exposure. It can assist physicians to detect changes in an individual's biochemistry before exposure to certain toxins.
Keywords: Radio-induced liver injury; Annual average effective radiation doses; Liver enzymes; Machine Learning (ML) Model

INTRODUCTION

Exposure to ionizing radiation from medical radiation equipment during diagnosis and cancer treatments can impact the biochemistry of hospital workers by initiating the process of oxidative stress. A liver is a radiosensitive organ that can have damaging impacts from radiation-induced oxidative stress[1-6]. The current study was conducted to see if there is any correlation exists between the exposure to ionizing radiation (IR) exposure and liver enzymes in medical radiation workers of INMOL (Institute of Nuclear Medicine and Oncology) Hospital, Pakistan during 2015-2020.An algorithm of Simple-Linear-Regression through machine learning (ML) approach was applied to develop the regression model to assess liver enzymes' impact with occupational low-does IR exposure. The machine learning (ML) approach of Artificial Intelligence (AI) is now widely used to build models and make predictions for useful conclusions in clinical medicine. The real processes can be approximated and solved analytically with linear models. The most important concept of ML includes predictive models[7]. We used the regression learning model to predict the influence on liver enzymes (AST-aspartate aminotransferase and ALT-alanine transaminasefrom exposure to low-dose radiations.

The objective of the study was to develop a Simple-Linear-Regression algorithm with supervised learning applied to find the correlation between liver enzymes with the AAED (mSv) in low-dose medical radiation workers.

MATERIALS AND METHODS

Sampling Technique: A sample size was calculated from calculator.net with the following parameters: confidence level: 90%, margin of error: 5%, population proportion: 90% and population size: 15,0000.
Inclusion & Exclusion Criteria: A total of 90 healthy radiation workers (age between 25-50 years) from the Radiology & Nuclear Medicine Departments of INMOL (Institute of Nuclear Medicine and Oncology) Hospital were included voluntarily. The included participants were working on the radiation equipment for 10 years. Individuals were not included those who were found with any hepatitis disease, and with any bacterial, viral, or fungal infections. Individuals with any cardiac issues, or chronic liver or kidney diseases were also excluded.
Ethical permission was obtained from Institutional Ethical Review Board.
Assessment of Annual Average Effective Radiation (AAED) Doses: A thermoluminescent dosimeter reader was used to assess the whole-body AAED (annual average effective radiation doses) in mSv. The radiation doses in Radiology and Nuclear Medicine departments were measured by Radiation Dosimetry Laboratory[8-10]. A software 'RaDLab' was used to calculate doses and to keep the histories[10].
Liver Function Test (LFT): The liver function tests were conducted for included radiation-exposed workers in the biochemistry lab of the INMOL Hospital. The liver enzymes AST-aspartate aminotransferase (U/L) and ALT-alanine transaminase (U/L) were considered for the models.
Correlation & Regression through Machine Learning (ML) Algorithm: We used the regression learning model to predict the influence on liver enzymes from exposure to low-dose radiations.A Simple-Linear-Regression algorithm with supervised learning was applied to find the correlation between liver enzymes (dependent parameters) with the independent variable, i.e., AAED (mSv) in radiation-exposed people (n=90). ML-based Simple-Linear-Regression algorithm learns a simple linear regression model. It picks the attribute that results in the lowest squared error. Its interface is a Weighted Instances Handler. From the given training set {$X_{1:n}$, $Y_{1:n}$}, a model can be learned model to how the inputs affect the outputs. With this model and a new value of X_{n+1}, the model can make a prediction $\hat{y}(x_{n+1})$. In general, the linear model can be expressed as: $\hat{y}\sum_{j=1}^{d} xij\ \theta j$ [11]. The correlation coefficients (R), mean absolute errors and root mean squared errors were noted for both the training set and data set. The model Simple-Linear-Regression developed the regression equations to predict the influence on liver enzymes from exposure to radiation (AAED) doses. The regression equations described the intercepts, slopes, and variances. The training data was comprised of at least 100 samples. The data set was comprised of at least 30 samples. Finally, the regression plots were also generated. The regression models were also cross-validated (10 folds) to affirm the mean absolute errors and root mean squared errors.

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RESULTS

Annual Average Effective Radiation (AAED) Doses: The mean value of the radiation dose was 0.28 mSv. The medical radiation was exposed to low-dose AAEDs in the range 0.05–1.12mSv during 2015-2020, which is well below (<20 mSv; averaged over five consecutive years) the limit implied by UNCEAR and ICRP.

ALT and AST Levels: The abnormal (high) levels of ALT were found in 50% (mean 65 U/L) of the workers, whereas, the altered raised levels of AST (40 U/L) were found in almost 25% of them.

Simple-Linear-Regression Model between AAED (mSv) and Liver Enzymes: The correlations and regression analyses were performed with the 'Simple-Linear-Regression' algorithm to predict the influence of AAED (mSv) on the liver enzymes Alanine Transaminase (ALT) and Aspartate Transaminase (AST) in radiation-exposed personnel.

Table 1 describes the detail of correlation coefficients, errors, and regression equations for both types of datasets, i.e., training dataset and test dataset in both ALT and AST models. The correlation coefficients in both types of datasets for both ALT/AST were almost found similar with similar values of mean errors and regression equation. Further, similar mean errors and regression equations were found on the split-percentage data (70% training and 30% data set) and also on cross-validation of 10 folds. Figures 1a & 1b show the pairwise scatter plots between AAED (mSv) and liver enzymes ALT/AST.

Liver enzymes ALT (R^2= 0.030) & AST (R^2= 0.00073) were having very weak relationships with annual average effective dose (AAED) in mSv. From regression equations, it is inferred that for every unit increase in AAED (mSv), there will be a 12.98 unit increase in ALT (U/L) values and a 0.63 unit increase in AST (U/L) values.

Figure 1 (a) Right: Pairwise scatter plots of data (AAED & ALT); (b) Left: Pair-wise scatter plots of data (AAED & AST)

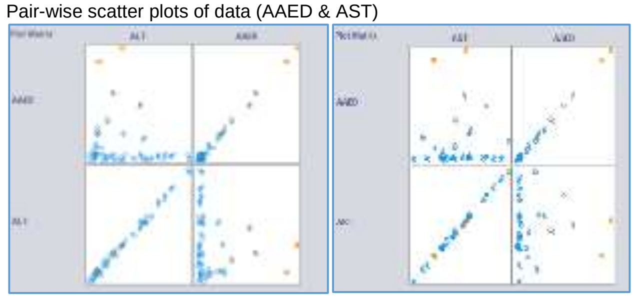

Table 1: Comparison of errors in ALT/AST Simple-Linear-Regression Machine Learning Models

ALT Model, Correlation Coefficient:R=0.1759;R^2=0.030 Regression Equation: *12.98 * AAED + 48.11*			
Training	**Dataset**	**Cross Validation**	**Percentage Split**
MAE= 18.0357 RMSE =21.6119	MAE= 17.9323 RMSE =21.6316	MAE= 18.3612 RMSE =21.8866	MAE= 18.2655 RMSE =21.9082
AST Model, Correlation Coefficient: R=0.0269; R^2=0.00073 Regression Equation: *0.63 * AAED + 28.74*			
MAE= 5.1962 RMSE =6.4441	MAE= 5.1962 RMSE =6.4441	MAE= 5.3185 RMSE =6.5628	MAE= 6.3161 RMSE =7.8985

DISCUSSION

The study identified that the medical radiation workers were exposed to small radiation doses. The mean value of the exposure dose was quite less than the permissible limit (<20 mSv) imposed by UNSCEAR and ICRP. The ALT parameter was found to have elevated values above the normal range in half of the radiation workers.The current research effectively validated a Simple-Linear-Regression model derived from machine learning (ML) techniques to predict any pre-abnormality in liver enzymes caused by occupational low doses of IR. The developed model revealed that the correlation between exposed radiation doses with liver enzymes is weak. Nonetheless, research implies that higher radiation doses can cause an increase in liver enzymes. The model was well validated as well to confirm the results. It is widely recognized that Artificial Intelligence (AI) Machine Learning (ML) models can be used securely to solve complicated biological systems[12]. Radiation can cause hepatic damage, which can result in liver cancer[13]. Exposure to X-rays has been shown to have an effect on liver enzymes, and the National Research Council's BEIR-V Committee indicated that long-term radiation exposure can cause liver cancer[14]. We discovered that around half of the medical radiation employees had elevated ALT levels (Alanine Transaminase). Radiation exposure has been linked to liver damage and an increased risk of hepatic cancer[15]. A hepatic metabolic change and radiation-induced carbonylation of liver enzymes were also found at IR doses up to 10 Gy[16].

Raised levels of liver enzymes might be detected in a short period of time and as a result of various health issues. Despite this, our radiation-exposed workers have moderate-to-high levels of ALT and AST. This may not necessarily signal substantial liver damage, but because the liver is considered a radiosensitive organ, we should continue to evaluate the hepatic function of occupational radiation employees as a preventative step. Although the exposed radiation dose was less than the limit, still chronic or long-term exposure can pose serious late health effects. Therefore, a caution of protection from radiation exposure should be taken[17]. Shahid et al. also applied three supervised learning machine learning models such as multilayer perceptron, logistic regression, and random forest to check if the radiation-exposed subjects were having altered liver functions from their radiation works. For the prediction of scores for liver function diagnostics, a machine learning technique was used by Patnik et al (2022)[18].

Four regression approaches are used to predict clinical ratings utilizing data from breath biomarkers as features provided using machine learning algorithms. The application of machine learning to predict scores proved to be extremely promising for the use of breath biomarkers for liver function diagnostics. Ahn et al. (2022)[19] also investigated machine learning models which efficiently differentiated patients with acute cholangitis and alcohol-associated hepatitis with laboratory tests. Liver disease is a major public health issue. The most accessible test for diagnosing liver illness is the liver function test (LFT). The majority of liver disorders present as elevated LFT. LFT data can be used to screen for liver disease and aid in computer-aided diagnosis. Yao et al (2020)[20] proposed a densely connected deep neural network (DenseDNN) for liver disease screening based on the 13 most regularly used LFT markers and demographic information from individuals. Deep learning models outperform traditional approaches in terms of performance.

CONCLUSION & RECOMMENDATION

The machine learning (ML) model we created for predicting the modification or abnormality in the liver enzymes due to radiation exposure was effectively deployed. The created model can help us understand the effects of low-dose ionizing radiation exposure on the liver. It can assist doctors in pre-diagnose any changes in a person's biochemistry before they are exposed to certain harmful substances. The liver is a radiosensitive organ and the ionizing radiations are hazardous, thus professionals in the medical field who are exposed to radiation should have their liver function checked often.

Conflict of interest: Nothing to be declared

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