A Cohort Study On Oxidative Stress Indications In Children Exposed To Cell Phone and Cell Tower Radiation

Meghana V
Dept. of AI and ML
Moodlakatte Institue of Technology, Kundapura
Udupi, India
meghanavinaykumar2003@gmail.com

K Dileep
Dept. of AI and ML
Moodlakatte Institue of Technology, Kundapura
Udupi, India
kdileepnaik@gmail.com

Indravijay Singh
Dept. of AI and ML
Moodlakatte Institue of Technology, Kundapura
Udupi, India
vijaysinghmgm35@gmail.com

Amlan Basu
Dept. of Electronics and Electrical Engineering
University of Strathclyde
Glasgow, U.K.
amlan.basu@strath.ac.uk

***Abstract*— This study investigates oxidative stress in children exposed to cell phone and cell tower radiation by developing a predictive model for Superoxide Dismutase (SOD) activity by analyzing key parameter radiation exposure levels and fibrinogen concentration to predict SOD activity. A neural network model with polynomial feature transformation was implemented to capture non-linear relationships between exposure and oxidative stress markers. The model achieved an R^2 of 0.9096, with mean absolute error (MAE) of 0.7863, mean squared error (MSE) of 0.8273, and root mean squared error (RMSE) of 0.9955**

Keywords—Neural Network Model, Superoxide Dismutase(SOD), Fibrinogen Concentration, Oxidative Stress.

I. Introduction

With the rapid technological advancements and widespread use of wireless communication devices, exposure to electromagnetic radiation (EMR) has become a daily reality. Mobile phones and cell towers emit non-ionizing radiation, which, although lower in energy than ionizing radiation, has been shown to influence biological systems

Oxidative stress is a condition that occurs when the body has many free radicals and not enough antioxidants to neutralize them. In recent years children are highly addicted to cell phones and exposed to cell towers radiation. These cell towers cause Electromagnetic radiation among children. These radiation affects the children health and mind. So this paper is all about the oxidative stress indications in children exposed to cell phone and cell tower radiation using the Superoxide Dismutase (SOD) as biomarkers. Radiation exposure levels and fibrinogen concentration as it's parameter.

In order to forecast oxidative stress levels and categorize exposure thresholds, this study makes use of sophisticated machine learning approaches, such as neural network regression models with polynomial feature transformation.
Aim is to create an accurate model that can predict SOD activity and assessing oxidative stress when exposed to radiation. The use of neural networks, combined with polynomial features, allows for a robust and flexible approach to a biologically complex problem. In conclusion, this approach integrates multiple steps—data preprocessing, feature engineering, model development, and training—to create a robust neural network model capable of predicting oxidative stress. By using polynomial features and standardizing the data, the model is well-equipped to capture complex, nonlinear relationships between the variables, while the use of an appropriate loss function and optimizer ensures efficient learning and accurate predictions

II. Literature Review

A. Mechanism of oxidative stress

Both ionizing and non-ionizing radiation cause oxidative stress by raising ROS levels, which upsets the equilibrium between antioxidant defenses and ROS synthesis.
DNA, proteins, lipids, and organelles like mitochondria are all impacted by this imbalance, which causes cellular damage.[1]

B. Health Impacts

When the human body is exposed to EMR, it absorbs the radiationbecause the human body is made up of 70% liquid. The human body size is much larger than the wavelength of the transmitting frequen cies of mobile phone towers, so there are multiple resonances in the body, which create local heating in the body [2]

Recent epidemiological studies have highlighted the role of cell phone exposure on sperm motility, morphology and viability,thus proposing a reduction in the fertilizing potential of males. However, the impact of these studies is low due to a lack of a control population (men who do not use cell phones), which would be extremely difficult to create. Additionally, an in vivo human exposure study to investigate the effects of cell phone radiation on semen parameters is not feasible due to ethical issues.[3]

Oxidative stress will be associated with the severity of depression in children and adolescents and that omega-3 fatty acid supplementation may influence the markers of oxidative stress [4].

Oxidative stress can be responsible for the induction of several diseases, both chronic and degenerative, as well as speeding up body aging process and cause acute pathologies [5]

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C. Community and Environmental Issues:

Communities are frequently exposed to dangerously high radiation levels when they are close to mobile towers. In crowded places, health risks are made worse by regulatory infractions and a lack of public knowledge.

D. Preventive Actions

Antioxidants, such as vitamin C, catalase, and melatonin, have shown promise in reducing oxidative stress brought on by radiation. Restoring cellular redox equilibrium and neutralizing ROS are the main goals of interventions.

E. How this paper differs

The previous reviews detects oxidative stress based on the data such as the measure of fibrinogen and radiation separately, but this paper deals with detection making use of the fibrinogen and radiation analysis combined and predicts superoxide dismutus by employing a neural network regression model and decision tree algorithm with polynomial feature transformation to predict SOD activity and assess oxidative stress.
The inclusion of threshold-based classifications to determine whether individuals are exposed to oxidative stress introduces a practical and scalable framework for assessing risk, unlike the general associations discussed in the literature.

III. Methodology And Implementation

A. Datasets

Data is collected from various people who were kept under observation with continuous monitoring in MGM hospital, Mumbai. We have used 2 parameters radiation and fibrinogen, in our study. Radiation refers to the energy emitted as electromagnetic waves or particles. Radiation exposure generates free radicals, specifically reactive oxygen species (ROS), that overwhelm the cell's antioxidant defenses, leading to oxidative stress. This stress triggers the upregulation of antioxidant enzymes like SOD.
Fibrinogen is a blood plasma protein primarily involved in clotting. However, fibrinogen also plays roles in inflammation and as a biomarker for various diseases.
The radiation exposure can increase fibrinogen levels as part of the body's inflammatory response. Thus, individuals exposed to high radiation levels might also exhibit increased fibrinogen, further linking the two factors to oxidative stress. SOD is an enzyme that catalyzes the breakdown of superoxide radicals, a type of ROS, into oxygen and hydrogen peroxide. This process is crucial in reducing oxidative stress within cells.
High radiation exposure and elevated fibrinogen levels both elevate oxidative stress. SOD activity can be upregulated as a protective response to such stressors. An increase in SOD activity indicates the body's attempt to manage excessive ROS. However, if oxidative stress continues unchecked, even elevated SOD levels may not be sufficient, leading to cellular and tissue damage.is crucial in reducing oxidative stress within cells.

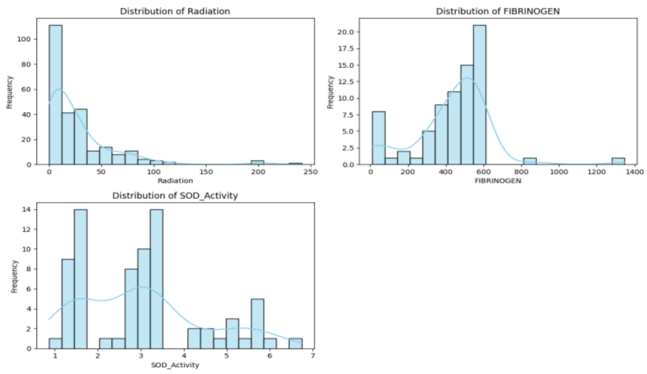

Fig 1: Distribution of various features in the dataset

Fig 1 displays the distribution of radiation histogram most people are exposed to lower radiation level i.e 0 to 50 range and only less people are exposed to radiation level above 150.In Distribution of Fibrinogen histogram variation is more than radiaiton it has 2 groups one for lower fibrinogen (ranges from 200-300) and higher fibrinogen (range-600) only few samples have reached 1400 fibrinogen level.

B. Neural Network Regression Model

Neural Network regression model to predict Superoxide Dismutase (SOD) activity based on the input features Radiation and Fibrinogen levels. To capture the non-linear relationships in the data, polynomial feature transformation was applied, followed by feature standardization to normalize the input. The neural network consists of dense layers with ReLU activation functions, designed to learn complex patterns from the data. The model is trained using the Adam optimizer, and Mean Squared Error is used as the loss function. The predicted SOD activity is classified into categories of oxidative stress exposure using a threshold-based approach. Thus, this methodology integrates regression and classification techniques in order to provide a wide predictive solution.
To further enhance the utility of the model, continuous predictions of SOD activity are grouped into binary categories as "Exposed to Oxidative Stress" or "Not Exposed" based on the threshold-based approach. Therefore, this model integrates the regression and classification approach to be able to deliver both very accurate numerical predictions and actionable classification for medical assessment.
Table 1 shows a summary of the major attributes used within this work. The first attribute, Radiation, is the amount of radiation dose that was undergone by the subjects and is in continuous numeric values. The second attribute, Fibrinogen, is a plasma protein critical for clotting blood, and typically in numeric ranges from 100 to 700 mg/dL. Lastly, SOD_Activity stands for the Superoxide Dismutase enzyme activity, measured in units per milligram of protein, which plays a crucial role in reducing oxidative stress by eliminating free radicals.

Radiation and Fibrinogen are input variable, SOD_activity is considered as target variable.The relationship between these columns is nonlinear so polynomial transformation should be applied. Standardize the given data to check input features are on similar scale and was applied to polynomial features to ensure they have mean of 0 and standard deviation of 1.Here 80% of data is considered for training the data and 20% of data is considered for testing the data.

TABLE I. DESCRIPTION OF FEATURES

Sl.No	Attribute	Description	Values
1	Radiation	The level of radiation exposure experienced by the subject.	Numeric values, typically continuous (e.g., 0 to 1000)
2	Fibrinogen	The concentration of fibrinogen, a plasma protein involved in clotting. High levels may indicate inflammation or cardiovascular risk.	Numeric values (e.g., 100 to 700 mg/dL)
3	SOD_Activity	Superoxide Dismutase (SOD) enzyme activity, which plays a key role in reducing oxidative stress by neutralizing free radicals.	Numeric values (e.g., 0 to 100 U/mg of protein)

Build a neural network model which consists of three layers i.e. input layer, hidden layers and output layer. There is one Input layer which accepts vectors of factors, There are multiple hidden layers, first hidden layer has 64 neurons along with relu activation function, second hidden layer has 34 neurons along with activation function.relu activation function is used in neural network because it allows the network to learn complex patterns. There is one output layer which has one neuron and no activation function and represents the predicted SOD activity.

Mean Squared Error is used as a loss function and adam optimiser is used. Model is trained for 100 epochs so that it passes through the entire dataset 100 times and batch size of 10 was selected and that for each epoch, the model updates weights after every 10 samples and set the SOD_threshold to 3.5.

C. Decision Tree

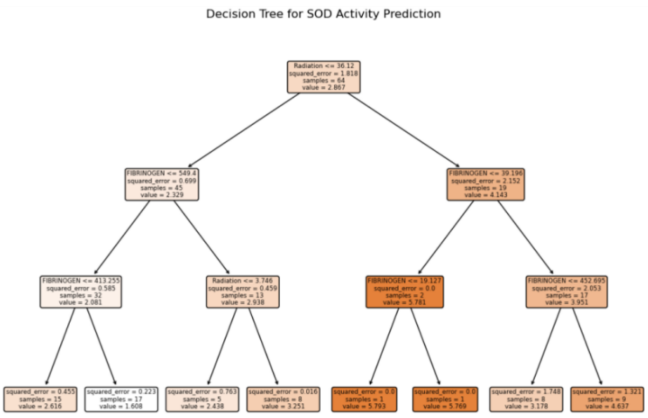

Fig 2: Decision tree

In Fig 2 there are three nodes root node, internal node and leaf node. The decision tree starts with a Radiation <= 36.12. Total number of samples is 64 and value is 2.87.The internal node represents either fibrinogen and radiation that further splits the data based on the predicted value. Leaf nodes are terminal nodes where no further splitting occurs. Each leaf node provides a final prediction.Each node shows squared error,values and samples.

IV. RESULT

A. *Correlation heatmap*

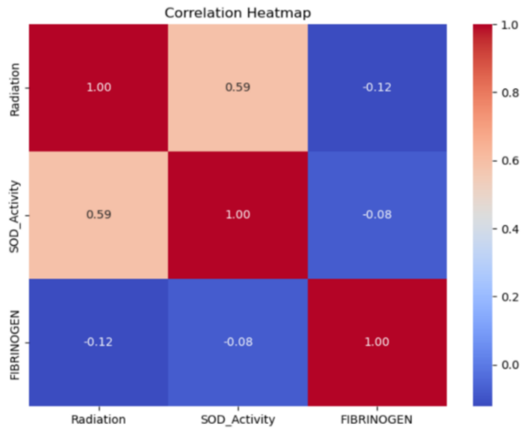

Fig 3 : Correlation heatmap

Fig 3 displays the relationship between three variables Radiation, SOD_activity and fibrinogen. There is positive correlation of 0.59 between radiation and SOD_activity, so if radiation activity increases SOD_activity will also increase. There is a negative correlation of –0.12 between radiation and fibrinogen so if radiation increases there will be decrease in fibrinogen level. There is a week correlation of –0.08 between SOD_activity and fibrinogen. Diagonal values represent correlation itself is always 1

TABLE II. MODEL PERFORMANCE

Mean Absolute Error (MAE)	0.7863
Mean Squared Error (MSE)	0.8273
Root Mean Squared Error (RMSE)	0.9096

Table 2 summarizes the performance metrics of the predictive model. The Mean Absolute Error is 0.7863, which is the average magnitude of errors, giving an indication that the predictions are about 0.79 units away from the actual values. The Mean Squared Error is the average of the squared prediction errors and amounts to 0.8273, suggesting the model is relatively sensitive to larger errors. Last but not least, the Root Mean Squared Error (RMSE) is 0.9096, which gives the standard deviation of prediction errors, an overall measure of prediction accuracy. These metrics reflect the model's ability to predict SOD activity based on input features.

B. *Training and Validation Loss Over Epochs*

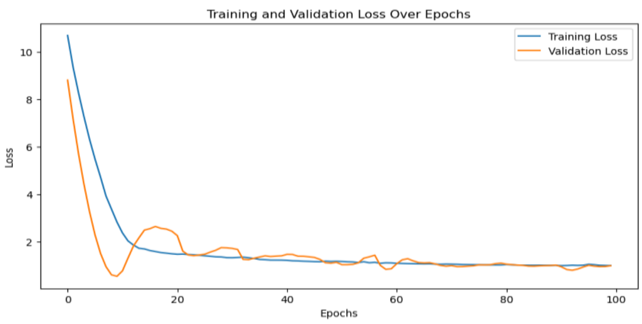

Fig 4 : Training and Validation Loss Graph

Fig 4 represents training and validation loss. The blue line represents training loss graph .It starts high and then decreases as the model learns The orange line represents validation loss which is not used for training. Initially, it decreases quickly. Around the 20th epoch, it fluctuates but remains close to the training loss, indicating that the model is not overfitting.Model has testing and validation accuracy of 84.62%.

TABLE III. CLASSIFICATION REPORT

	precision	recall	F1score	Support
Not exposed	1.00	0.82	0.90	11
Exposed	0.50	1.00	0.67	2
Accuracy			0.85	13
Macro Avg	0.75	0.91	0.78	13
Weighted avg	0.92	0.85	0.86	13

Table 3 reports the evaluation of the classification model. Precision : 1.00 - all predictions were correct for the class Not Exposed; recall : 0.82 (or 82% of actual cases were correctly classified); F1 : 0.90, balancing precision and recall. For the class Exposed, precision was lower at 0.50, but recall was 1.00, which means all of actual cases of this class are identified, even if with more false positives. The model is 85% accurate, meaning it correctly classified 85% of the instances. Both the Macro Average and the Weighted Average, calculated as unweighted mean across classes and weighted mean considering class support respectively, and though balanced clearly reveal a stronger performance on the majority class, Not Exposed, with F1 scores at 0.78 and 0.86, respectively.

C. Function to classify oxidative stress based on user input

Input 1:

Prepare the input data with polynomial transformation and scaling. Classify based on threshold. As we have considered Radiation and Fibrinogen as input vairable so get user input for Radiation and Fibrinogen and use the function to classify oxidative stress based on user input and plot the graph between User's SOD Activity Prediction and Oxidative Stress Threshold.

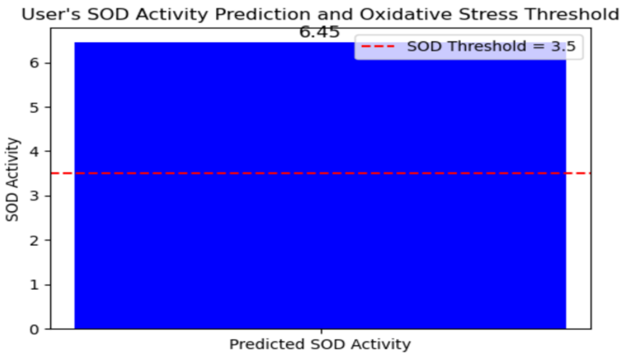

Fig 5: Exposed to oxidative stress plot based on new input

Fig 5 tells whether the new input is exposed to oxidative stress or not .X axis represents SOD_activity and Y axis represents Predicted SOD_activity .If the predicted SOD_activity of the given input is higher than the threshold SOD then the exposure status will be "Exposed to Oxidative stress". In this case assume the user has given 100 for level of radiation and 20 for level of fibrinogen then the Predicted SOD will be 6.45 and when compared with SOD threshold (SOD_activity=3.5) predicted SOD is more so the exposure status will be "Exposed to Oxidative stress".

Input 2:

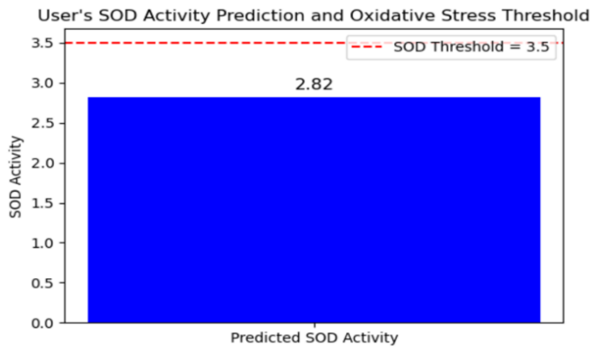

Fig 6: Not Exposed to oxidative stress plot based on the input

Fig 6 shows when the new input is not exposed to oxidative stress.X axis represents SOD_activity and Y axis represents Predicted SOD_activity of the predicted SOD_activity.If the given input is lower than the threshold SOD then the exposure status will be "Not Exposed to Oxidative stress"In this case Predicted SOD is 2.78 and SOD threshold is 3.5 so predicted SOD hence exposure status will be "Exposed to Oxidative stress".

VI. CONCLUSION

The objective was to develop a precise and valid model for predicting SOD activity and assessing oxidative stress in children exposed to high levels of radiation. In fact, the task is important because oxidative stress plays an influential role in health problems, especially in the exposure of subjects to radiation. By using advanced machine learning techniques, the project uses neural networks with polynomial feature transformation to capture the non-linear relationships between radiation, fibrinogen levels, and SOD activity. This ensures that the model is able to cope with intricate biological interactions in the data.

The neural network model balances performance in predicting SOD activity and in classifying exposure to oxidative stress. Important metrics of the model are MAE, MSE, and accuracy that show efficacy of the model.The introduction of polynomial features further brings flexibility as they enable the model to better grasp complex patterns existing in the data.Although the classification accuracy is reported to be 85%, yet the study shows that there is need to fine-tune the model by improving class imbalance. In general, this research enhances the possibility of machine learning in biomedical applications to provide more personal and effective means of health monitoring. For the future work following points could be considered,

- Instead of few parameters to predict SOD_activity and oxidative stress in the future the parameters can be increased.
- Conduct comparative studies between urban and rural settings to assess the impact of varying EMR exposure levels and environmental conditions on oxidative stress.
- Enhance the predictive model by exploring additional machine learning techniques, such as ensemble methods or deep learning, to improve the accuracy and generalizability of oxidative stress predictions.
- While existing studies explore the effects of EMR on general health, including fertility and neurological functions, there is limited research specifically targeting children, who are frequent users of mobile devices and are often exposed to nearby cell towers.

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