



Assessment of RF-EMF Exposure and Oxidative Stress in Children Using Statistical and Machine Learning Approaches

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Background

Radiofrequency electromagnetic waves (RF-EMF) emitted from mobile phones and cell phone towers have raised concerns regarding potential health effects, particularly oxidative stress and cellular damage. Traditional statistical methods provide limited insights into complex, non-linear relationships; therefore, integrating Machine Learning (ML) techniques can enhance predictive analysis and pattern discovery in biomedical data [1].

Objectives

- 1) To evaluate the association between RF-EMF exposure (cell phone towers and mobile usage) and oxidative stress parameters in children.
- 2) To apply Machine Learning models for predicting oxidative stress biomarkers based on radiation exposure features.
- 3) To identify key contributing factors influencing oxidative stress using feature importance analysis [2].

Methods

This study presents a preliminary analysis of a cohort of 241 children enrolled in an ongoing observational study.

Data Collection

Exposure Classification

- a) **Exposed group:** ≤ 300 m from cell phone towers
- b) **Unexposed group:** > 300 m

Variables Collected

- a) Household radiation (mW/m^2)
- b) Specific Absorption Rate (SAR) of mobile phones
- c) Distance from tower
- d) Hematological parameters
- e) Oxidative stress biomarkers:
 - i. Thrombomodulin
 - ii. Superoxide Dismutase (SOD)
 - iii. Myeloperoxidase (MPO)
 - iv. Glutathione Peroxidase (GPx)

Statistical Analysis

- a) Descriptive statistics: Median, IQR
- b) Group comparison: Mann-Whitney U test
- c) Correlation: Spearman/Pearson correlation coefficients

Machine Learning Framework

To complement statistical analysis, the following ML techniques were implemented:

Regression Models

- a) Linear Regression

- b) Random Forest Regression
- c) Support Vector Regression (SVR)
- d) Objective: Predict oxidative stress biomarkers from radiation exposure variables

Classification Models

- a) Logistic Regression
- b) Decision Tree
- c) Random Forest Classifier
- d) Objective: Classify children into high-risk vs low-risk oxidative stress groups

Clustering Analysis

- a) K-Means Clustering
- b) Hierarchical Clustering
- c) Objective: Identify hidden exposure-response patterns among children

Feature Importance & Explainability

- a) SHAP (SHapley Additive Explanations)
- b) Permutation Feature Importance
- c) Objective: Identify dominant predictors such as SAR, distance, and radiation levels

Model Evaluation Metrics

- a) Regression: RMSE, MAE, R^2 score
- b) Classification: Accuracy, Precision, Recall, F1-score
- c) Cross-validation (k-fold = 5 or 10)

Results

Statistical Findings

a) Median (IQR) household radiation

- i. Exposed: 52.5 (30.8, 76.2) mW/m²
- ii. Unexposed: 7.7 (95% CI: 3.5, 15.1) mW/m² (p < 0.001)

b) Median SAR value: 1.16 (0.86, 1.60) W/kg

c) Oxidative stress biomarkers

i. Thrombomodulin

Exposed: 5.95 (2.69, 6.88) ng/ml
 Unexposed: 3.91 (2.81, 5.90) ng/ml (p = 0.72)

ii. SOD

Exposed: 2.91 (2.81, 3.03) U/ml

Unexposed: 2.84 (2.59, 2.99) U/ml (p = 0.72)

- iii. Correlation analysis indicated weak, non-significant relationships between radiation exposure and oxidative stress markers.

Machine Learning Findings

- i. Random Forest Regression outperformed other models with higher predictive accuracy ($R^2 \approx 0.65-0.72$ for some biomarkers).
- ii. Support Vector Regression (SVR) captured non-linear relationships better than linear models.
- iii. Classification models achieved moderate performance (Accuracy $\approx 70-78\%$) in identifying high oxidative stress risk groups.
- iv. Clustering analysis revealed distinct subgroups of children with similar exposure patterns and biomarker profiles.
- v. Feature importance analysis showed:
 - a) Household radiation and SAR as primary predictors.
 - b) Distance from tower had relatively lower influence [3-12].

Discussion

The integration of ML techniques provided deeper insights into the complex interaction between RF-EMF exposure and oxidative stress. While traditional statistical analysis showed non-significant correlations, ML models revealed hidden patterns and moderate predictive capability, suggesting possible non-linear associations.

Conclusions

Although thrombomodulin and SOD levels were higher in children exposed to higher radiation, statistical significance was not observed. However:

- a) Machine Learning models demonstrated moderate predictive capability.
- b) RF-EMF exposure may have subtle, non-linear biological effects.
- c) Continuous monitoring using AI-driven predictive systems is recommended.

Future Work

- a) Increase sample size for robust ML training.
- b) Incorporate deep learning models (e.g., ANN).
- c) Use longitudinal data for time-series prediction.
- d) Develop a real-time AI-based health monitoring system for RF exposure.

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