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Mini Review

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/m^2

ii. Unexposed: 7.7 (95% CI: 3.5, 15.1) mW/m^2 ($p < 0.001$)

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 ≈ 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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