A Decision Support System for Managing Health Symptoms of Living Near Mobile Phone Base Stations

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ABSTRACT

Background: The rapid increase in the number of Mobile Phone Base Stations (MPBS) has raised global concerns about the potential adverse health effects of exposure to Radiofrequency Electromagnetic Fields (RF-EMF). The application of machine learning techniques can enable healthcare professionals and policymakers to proactively address concerns surrounding RF-EMF exposure near MPBS.

Objective: The current study aimed to investigate the potential of machine learning models for the prediction of health symptoms associated with RF-EMF exposure in individuals residing near MPBS.

Material and Methods: This analytical study utilized Support Vector Machine (SVM) and Random Forest (RF) algorithms, incorporating 11 predictors related to participants' living conditions. A total of 699 adults participated in the study, and model performance was assessed using sensitivity, specificity, accuracy, and the Area Under Curve (AUC).

Results: The SVM-based model demonstrated strong performance, with accuracies of 85.3%, 82%, 84%, 82.4%, and 65.1% for headache, sleep disturbance, dizziness, vertigo, and fatigue, respectively. The corresponding AUC values were 0.99, 0.98, 0.920, 0.89, and 0.81. Compared to the RF model and a previously developed model, the SVM-based model exhibited higher sensitivity, particularly for fatigue, with sensitivities of 70.0%, 83.4%, 85.3%, 73.0%, and 69.0% for these five health symptoms. Particularly for predicting fatigue, sensitivity and AUC were significantly improved (70% vs. 8% and 11.1% for SVM, Multilayer Perceptron Neural Network (MLPNN), and RF, respectively, and 0.81 vs. 0.62 and 0.64, for SVM, MLPNN, and RF, respectively).

Conclusion: Machine learning methods, specifically SVM, hold promise in effectively managing health symptoms in individuals residing near or planning to settle in the vicinity of MPBS.

Keywords

Artificial Intelligence; Electromagnetic Hypersensitivity (EHS); Electromagnetic Fields; Machine Learning; Mobile Phone Base Stations

Introduction

The rapid progress in wireless communication technologies has led to a significant increase in the general population's exposure to Electromagnetic Fields (EMFs). Individuals are now constantly exposed to various sources of EMFs, such as mobile phones, cordless phones, Wi-Fi routers, and power lines. Consequently, global

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concerns are rising regarding the potential adverse health effects of Electromagnetic Field (EMF) exposure. Researchers are actively investigating the impact of low-intensity EMFs on human health and other organisms.

Several studies have investigated the potential health effects of exposure to microwave radiation, EMFs, Radiofrequency (RF), and radiofrequency electromagnetic radiation [1-15]. Individuals living within <300 meters of mobile base stations reported more frequent symptoms of nausea, headache, dizziness, irritability, discomfort, nervousness, depression, sleep disturbance, memory loss, and diminished libido compared to those living further away (>300 meters) [16]. In a review published in 2010, 8 out of 10 studies through PubMed reported an increased prevalence of adverse neurobehavioral symptoms in populations living within <500 meters of base stations, as well as other effects, such as headache, fatigue, sleep disturbance, and poor concentration [5].

The potential adverse health effects of human exposure to radiofrequency electromagnetic fields, including long-term effects are well-documented. Jooyan and Mortazavi addressed the challenging issue of the carcinogenesis of radiofrequency radiation in their commentary published in JAMA Oncology and also highlighted the shortcomings of studies that do not support a potential link between exposure to radiofrequency radiation and increased cancer risk [17].

The exposure from broadcasting sites and base stations affects the entire body from a distance, while smartphones and smart gadgets only impact the head and hands in close proximity [18]. Recent studies show that mobile phone base stations are the primary source of the radiofrequency radiation spectrum [19]. In 2022, a review conducted on the effects of base station antennas on human health revealed three types of impacts: radiofrequency sickness, cancer, and changes in biochemical parameters. Among the globally reviewed 38 studies, 28 indicated some forms of effect, with radiofrequency sickness being the most prevalent, accounting for 73.9% of the cases [20]. A case study conducted in Stockholm showed the effects of Electromagnetic Hypersensitivity (EHS) near mobile phone base stations [21]. Epidemiology studies are the primary focus of RF research concerning human exposure, even though it is challenging to separate distance from a tower as an independent variable and determine actual exposure levels due to the prevalence of ELF and RF fields in daily life through personal wireless devices. This poses a potential weakness in such studies as it becomes difficult to find unexposed controls [22].

Given the exponential growth of wireless technology, developing a model to predict potential adverse health effects in advance could help minimize health hazards and symptoms for those living or planning to settle in close proximity to mobile phone base stations. Such models could also be used as a precautionary measure when setting mobile base stations to minimize potential health hazards.

Although the negative impacts on health caused by living close to MPBS have been extensively studied, there is a lack of reports on the use of artificial intelligence models to forecast subjective health symptoms in individuals residing or working near these stations. In the previous research, we introduced models based on Multilayer Perceptron Neural Networks (MLPNN) to anticipate subjective health symptoms in individuals living near cellular phone base stations [23]. The system provided promising results, but its sensitivity in predicting symptoms, such as fatigue was low. Therefore, a more accurate model is needed for early detection of health symptoms among individuals living near mobile stations.

In this work, we explored the possibility of developing a reliable and applicable model using the Support Vector Machines (SVM) algorithm, which has been shown to be a robust method for classification and pattern recognition [24], particularly effective in analyzing medical data [24-26]. The rest of this paper includes a brief discussion of the classifiers used, a description of the methodology, and the results and discussion sections.

To our knowledge, this initial research represents a pioneering effort in utilizing Support Vector Machines (SVM) to predict personal health symptoms among individuals living in proximity to mobile phone base stations, despite certain limitations such as relying on personal symptom accounts. The significant advantage of the SVM-based model developed in the present study lies in its outstanding performance in terms of accuracy and the Area Under the Curve (AUC).

Material and Methods

The objective of this "analytical study " was to develop a model for predicting the subjective health symptoms of individuals living near mobile base stations, with a focus on the five common complaints of headache, sleep disturbance, dizziness, vertigo, and fatigue. The desired model should determine whether an individual might have one or more of these symptoms. The development process included three main steps: data collection, data preprocessing, and model development.

Data collection

A total of 699 adults, consisting of 363 men (average age 32±13 years) and 336 women (average age 32±12 years), who lived near cellular phone base stations in 11 different districts of Shiraz, Iran, were included in this cross-sectional study. The participants were randomly selected, with 20% of the base stations in each random district. Buildings located within 1 km of the selected base stations were divided into four groups based on their distance from the nearest base station (D): 1) for distances less than 100 m, 2) for distances between 100 m and 300 m, 3) for distances between 300 m and 600 m, and 4) for distances between 600 m and 1000 m. These ranges were selected because individuals living within 300 m of a base station may experience symptoms, such as tiredness, headache, sleep disturbance, discomfort, irritability, depression, memory loss, dizziness, and decreased libido [16].

A questionnaire was administered, containing questions on demographic data, subjective complaints, and occupational and environmental exposure to different sources of electromagnetic fields. The average electric and magnetic field strengths were measured in each household using a recently calibrated EMF meter. Personal information, along with comprehensive details of the participants' lifestyles, was collected by trained interviewers. For each participant, age, gender, education level, mobile phone usage during the day/week/month, and the distance of the living/working place to the base station tower were recorded. In the end, a total of 11 parameters were documented to assess the living conditions of each participant. Subjective complaints, such as nausea, headache, dizziness, irritability, discomfort, nervousness, depression, sleep disturbance, memory loss, and diminished libido were noted. Prior to their involvement in the study, all participants provided written consent. The data collection process involved conducting measurements at participants' homes and conducting interviews in person.

Statistical analysis and data preprocessing

The objective of this step was to identify and eliminate outliers or unusual observations, as well as select the variables to be utilized in the model. To achieve this, graphical display methods such as scatterplots and box plots were employed, alongside quantitative techniques like the Interquartile Range (IQR). Inconsistent data, such as daily cellphone usage exceeding 24 hours, were considered unacceptable parameters. Each feature variable was normalized using the min-max scaling method (Equation 1), which scales the variables to a range of 0 to 1, as follows:

$$x' = \frac{x - min(x)}{\max(x) - min(x)} \quad (1)$$

where x and x' are the original and normalized values of a given variable, respectively.

Model Development

The model development process consisted of two main steps: feature selection and classification. The feature selection step aimed to identify relevant predictors and eliminate irrelevant ones. We utilized a neighborhood component analysis method, a non-parametric technique that estimates the relative weight of each variable by maximizing the expected classification accuracy [27]. Ultimately, after the selection process, 11 parameters were identified related to the individuals' living status that proved effective for the model. The list of these parameters and a description of each one is provided in Table 1.

The model aimed to forecast subjective health symptoms in individuals residing close to mobile base stations by utilizing the 11 living status parameters described in Table 1. Specifically, the model aimed to determine whether a participant experienced one or more health symptoms, such as headache, sleep disturbance, dizziness, vertigo, and fatigue. This task belongs to the classification category in machine learning, where the class of a new sample is determined by leveraging known class labels within a given dataset. In the present study, SVM and RF algorithms were implemented to develop the desired prediction models. The models were developed using Matlab's Statistics and Machine Learning Toolbox (Mathworks, Natick MA, USA).

The SVM is a statistical supervised learning model that tackles common challenges in machine learning, such as overfitting and local minimum, by minimizing structural risk theory [28]. By minimizing an upper bound on the generalization error, the SVM effectively addresses the objective of reducing errors in statistical pattern recognition and automated estimation systems. We trained the SVM using the Sequential Minimal Optimization (SMO) method [29].

The RF algorithm generates multiple decision trees, with each tree incorporating random features. The trees are constructed by selecting the most informative features to separate classes, and the process recursively continues based on the dataset. Training in the random forest occurs through bagging and replace-

Table 1: The list of variables included in subjective health symptoms prediction model

Variable	Description
Age	Age (year), at the time of interview
Gender	Gender (male/female/not declared)
Mobile phone call time	Average daily call time (min)
History of mobile phone usage	Number of months of mobile phone usage
Cordless phone use	Average daily call time using cordless phones (min)
VDU use	Average daily use of Video Display Units (VDUs) (min)
Distance from base station	Distance from the nearest mobile base station (m)
Duration of residence	Duration of residence in the present house (month)
Exposure time	Average daily exposure time to mobile base stations (h)
Exposure to power lines	Living in the vicinity of a power line (yes/no)
Other wireless devices	Exposure to other sources of electromagnetic fields (yes/no)

ment, in which random subsets are selected from the dataset, and a tree is fitted to each subset. To classify a test sample, it is classified by each tree, and the outputs of the trees are combined for the final decision. The RF model employed 100 decision trees to create a forest, and the Gini impurity metric was used to measure attribute importance. Aggregating the outputs of the classifiers through majority voting is a common practice in the RF algorithm.

Model Evaluation

The performance of the developed model was quantitatively assessed using sensitivity, specificity, and accuracy indices. These indices provide measures to evaluate the accuracy and effectiveness of the classification process, determining the model's ability to correctly identify individuals with or without symptoms, as follows:

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \quad (2)$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \quad (3)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (4)$$

where TP and TN are the count of subjects accurately identified as having a symptom and not having a symptom, respectively. Also, FP and FN are the count of individuals without a symptom who are mistakenly identified as having a symptom and with a symptom who are mistakenly identified as not having a symptom, respectively.

To estimate these indices, the subjective complaints recorded during data collection were considered as the "gold standard" for training and testing the model. To ensure unbiased estimation and ultimately an unbiased evaluation of the model, the data were randomly divided into three parts: a training set comprising 75% of the data, a validation set with 5% of the data, and a test set containing 20% of the data.

The training set was used to find the support vectors and determine the parameters of the decision function [28]. The validation dataset was employed to select the optimal parameters for the model and optimize its performance by identifying the best values for regularization parameters, the kernel function, and its associated parameters.

The RF model was trained using the bagging method, which involves randomly sampling subsets of the training data, fitting a decision tree to each subset, and aggregating the predictions. This RF model utilizes the Gini impurity metric to measure the quality of nodes and branches to achieve the best results.

Finally, the test dataset was employed to evaluate the final model fitted to the training dataset. This evaluation involved comparing the predicted values for these examples with the actual values, providing a measure of the model's performance.

Results

After developing the models, their performance was evaluated using test data comprised of 140 samples. Four performance indices, namely sensitivity, specificity, accuracy, and AUC were utilized to assess the effectiveness of the models. The SVM-based model demonstrated excellent performance in predicting health symptoms, such as headache, sleep disturbance, dizziness, vertigo, and fatigue. For example, it achieved accuracies of 85.3%, 82%, 84%, 82.4%, and 65.1% respectively. The corresponding AUCs were 0.99, 0.98, 0.92, 0.89, and 0.81 respectively. Compared to the RF model and the previously developed model, the SVM-based model showed higher sensitivity (83.4%, 85.3%, 73%, 69%, and 70% for headache, sleep disturbance, dizziness, vertigo, and fatigue respectively). Significantly, the model demonstrated notable improvements in sensitivity and AUC for predicting fatigue. The sensitivity increased to 70% and the AUC improved to 0.81. In comparison, the MLPNN model achieved a sensitivity of only 8% and an AUC of 0.62, while the RF model achieved a sensitivity of 11.1% and an AUC of 0.64 [23].

Figure 1 presents the relative attribute importance for the variables included in the model. These numbers were estimated based on the average impurity for each class in the ratablendom forest algorithm. Figure 1 highlights three variables as the most important predictors of health symptoms: the distance from the mobile base station, the age of the participant, and the duration of residence in the area. Table 2 indicates that the SVM-based system demonstrates superior performance compared to other systems in predicting subjective health symptoms in the majority of cases, as evidenced by elevated sensitivity and AUC values.

Discussion

The aim of this study was to explore the potential of AI in predicting the health risks associated with exposure to EMF. The results obtained in this study demonstrate that the SVM-based system outperforms other systems in predicting subjective health symptoms for most cases, as indicated by higher sensitivity and AUC values. This finding is consistent with previous studies highlighting the effectiveness of SVM in classification problems [26, 30]. However, the accuracy in predicting fatigue symptoms using the SVM-based model is slightly lower than that of other symptoms. The observed discrepancy in the performance can be attributed to the multifactorial nature of fatigue. Thus, other variables, which are not considered in the models, may contribute to the prediction of fatigue, leading to the differences in performance.

A comparison between the SVM-based model and the previously developed MLPNN-

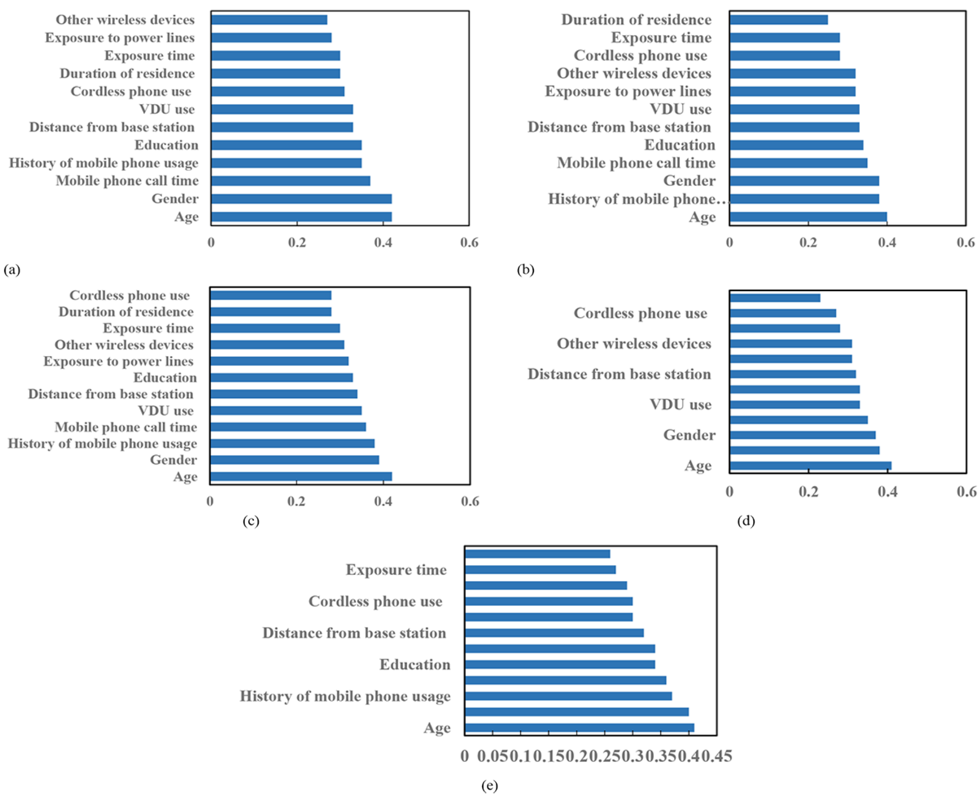

Figure 1: Relative Importance of Attributes for Subjective Health Symptoms Prediction Models Estimated Using RF Model. (**a**) headache; (**b**) dizziness; (**c**) sleep disturbance; (**d**) fatigue (**e**) vertigo. (RF: Radiofrequency, VDU: Video Display Unit)

Table 2: Performance Comparison of Prediction Models for Subjective Health Symptoms in Individuals Residing Near Mobile Phone Base Stations: SVM, MLPNN, and RF Models. (SVM: Support Vector Machine, MLPNN: Multilayer Perceptron Neural Network, RF: Radiofrequency)

Symptom	Sensitivity (%)			Specificity (%)			Accuracy (%)			AUC		
	MLPNN	SVM	RF	MLPNN	SVM	RF	MLPNN	SVM	RF	MLPNN	SVM	RF
Headache	71.8	83.4	75.1	90.9	85.5	93.4	83.8	85.3	86.7	0.95	0.99	0.98
Sleep disturbance	82.1	85.3	71.1	83.3	82.1	91.9	82.9	82.0	85.9	0.96	0.98	0.95
Dizziness	65.2	73.0	67.3	85.4	84.6	94.9	81.0	84.0	89.0	0.88	0.92	0.95
Vertigo	65.0	69.0	52.2	84.7	83.5	91.3	81.0	82.4	81.3	0.87	0.89	0.84
Fatigue	8.0	70.0	11.1	98.9	68.6	97.9	88.6	65.1	84.5	0.62	0.81	0.64

AUC: Area Under the Curve, MLPNN: Multilayer Perceptron Neural Network, SVM: Support Vector Machine, RF: Radiofrequency

based model revealed that SVM's superior performance can be attributed to its focus on minimizing generalization errors during training [23]. In contrast, MLPNNs tend to overfit the training data, resulting in lower performance on unseen data. These results align with previous research highlighting SVM's capability in classification problems [26, 30].

There is one exception observed in Table 2, in which the accuracy of the SVM in predicting fatigue symptoms is lower than both the MLPNN-based model and RF-based model. However, the sensitivity of the SVM-based model for fatigue symptoms is significantly higher than that of the other models [23]. The trade-off between sensitivity and accuracy shows that enhancing one metric may result in a compromise with the other. In this study, we tackled this trade-off by incorporating class weights during the classifier training process. Specifically, we assigned higher costs to false negative errors compared to false positive errors (FN=2FP). As a result, the SVM model achieved a higher AUC value for predicting fatigue symptoms compared to the other models.

The relative attribute importance results for the variables (Figure 1) indicate that "age" and "gender" have the most significant influence on health symptoms. Additionally, both "mobile usage factors (history and call time)" are among the top four influential parameters. However, the effect of other attributes on cognitive symptoms is also comparable to that of the most important one. These findings are consistent with previously published works that reported "mobile phone usage" and "age" as among the top four influential features for each cognitive symptom [23].

From a broader standpoint, our findings are in line with studies that have reported that while there is an increasing concern regarding the potential negative health consequences of RF-EMF exposures from mobile phone base stations, the health complaints of individuals living near these base stations cannot be fully explained by these concerns alone [31]. Notably, previous large population-based studies have shown that residents who were concerned about or attributed detrimental biological effects of RF-EMF generated by mobile phone base stations, as well as those living closer to the base station (e.g., <500 m), had more health complaints compared to others [31]. Furthermore, our results support reports showing the presence of sleep disturbances, headaches, dizziness, irritability, concentration difficulties, and hypertension in the majority of people residing near mobile phone base stations [32]. Additionally, the obtained results align with reports indicating a higher risk of developing neuropsychiatric problems in individuals living in the vicinity of mobile phone base stations. Headache, memory changes, dizziness, tremors, depressive symptoms, and sleep disturbance have been reported to be significantly higher in individuals living around mobile phone base stations [33].

Regarding the co-existence of proximity to power lines and mobile phone base stations, our results are in line with those of studies that associate perceived proximity to both with Non-specific Physical Symptoms. However, our findings contradict a limited number of studies that reported no significant association between measured RF-EMFs emitted from mobile phone base stations and adverse health effects [34].

The practical application of our study lies in utilizing AI to predict health risks associated with EMF exposure. By employing relatively simple and easily measurable variables as inputs, our model can predict the health status of individuals residing near cellular phone base stations. This predictive capability can help assess potential health risks for those currently living near these stations or individuals considering moving to such areas. Consequently, the model can contribute to the reduction of EMF-related health risks and inform decision-making processes related to the management and establishment of mobile base stations.

While this study presents promising results, it is essential to acknowledge its limitations. All variables, including both input and output variables, rely on self-reports, which introduce a degree of uncertainty in the values. Achieving accurate estimates for these parameters would require individual monitoring using specialized instruments, which may pose logistical challenges. However, the focus of this study was to develop a practical model using easily accessible variables. Furthermore, the findings should be considered preliminary, and further evaluation of the model's predictability and reliability is necessary using a more extensive dataset with long-term follow-up, such as a five-year study. Future research should also explore the inclusion of additional variables, such as weight, hours of sleep per night, general health, and socio-economic factors. Deep statistical analysis, such as multidimensional analysis, can provide deeper insights, and the model's performance should be assessed over an extended follow-up period.

Conclusion

The current study highlights that addressing the impact of microwave radiation on the human nervous system, and cognitive functions necessitates the consideration of multiple factors, such as environmental exposure to mobile phone base stations and individual health conditions. By harnessing the power of AI, healthcare providers can better understand and predict the health risks associated with EMF exposure, leading to delivering targeted interventions and supporting affected individuals. In this study, an SVM classifier was successfully implemented to predict five subjective health symptoms, surpassing the performance of a previously developed MLPNN-based model. The findings of this research underscore the potential of AI-based models in assisting healthcare professionals, including physicians, in effectively managing symptoms associated with EMF exposure in individuals living near mobile phone base stations. Future work should include additional variables, statistical analyses, and longer follow-up periods.

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Authors' Contribution

SMJ. Mortazavi and H. Parsaie conceived the idea. M. Faraz carried out the analysis. All the authors read, revised, and approved the final version of the manuscript.

Ethical Approval

The study was approved by the SUMS Committee of Medical Ethics (IR.SUMS.REC.1398.276).

Informed Consent

All participants gave their informed consent for inclusion in this study.

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Conflict of Interest

SMJ. Mortazavi, as the Editorial Board Member, was not involved in the peer-review and decision-making processes for this manuscript.

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