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Data Normalization Methods of Hybridized Multi-Stage Feature Selection Classification for 5G Base Station Antenna Health Effect Detection

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ABSTRACT

It is essential to assess human exposure to Fifth Generation (5G) Radiofrequency Electromagnetic Field (RF-EMF) signal from Base Station (BS) sources operating at Low Band 5G at 700 MHz, Sub-6 Band 5G at 3.5 GHz, and Millimeter Wave (mmWave) 5G at 28 GHz. This assessment will help determine whether 5G technology is safe for people. Inconsistent results were found in previous epidemiological studies on the health effects of radiation exposure from Mobile Phones (MP) and BS when normalization methods were used to prepare the data for Machine Learning (ML), which could lead to misclassification because of the dataset's quality. The effects on adult health are assessed in terms of physiological parameters (body temperature, heart rates, and blood pressure), cognitive performance (brain memory, motor control, and attention), Visual Analogue Scales (VAS) for well-being parameter, and Electromagnetic Field (EMF) perception parameter. The purpose of the research was to identify changes in the physiological parameters of adult individuals before, during, or after exposure to 5G signals, including Sham (No Exposure). 12 normalization methods are selected which are Z-score normalization (z score), Linear scaling (LS), Binary normalization (BNN), Bipolar normalization (BPN), Min-Max scaling (MMS), t-score normalization (t score), Decimal Inverse Logarithmic Scaled Normalization (DILSN), Relative Mean Normalization (RMN), Relative Standard Deviation Normalization (RSDN), Variation Normalization (VN), Robust Normalization (RN) and Relative Interquartile Normalization (RIN) and based on their F-value and p-value analyses, the three best normalization techniques are selected in this research. The original distribution of each parameter data variable is different, these techniques are beneficial for converting data so that it is dimensionless and has equivalent distributions. Based on the selection criteria for the hybridized Multi-Stage Feature Selection (MSFS) classification for 5G base station antenna health effect detection, BNN, MMS, and RSDN were named as the top three normalization techniques.

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1. Introduction

The 5G technology is expected to be the main enablers for high-speed wireless communication in the next several years. The number of mobile devices and connections reached 8.8 billion in 2018. With the advent of the Internet-of-Things (IoT), billions of connected devices are also being deployed. Both evolutions have a major impact on the Information and Communications Technology (ICT) usage and consequently, the economy. By 2023, the number of worldwide mobile devices will increase to 13.1 billion, with Fourth Generation (4G) and 5G generating 46% and 11% of global connections, respectively. With the increase of smartphones, Machine-to-Machine (M2M) connections, connected televisions, and tablets, the number of devices will reach 3.6 per capita [1] International Telecommunication Union (ITU) estimates that approximately 4.9 billion people or 63% of the world's population were using the Internet in 2021. This represents an increase of 17% since 2019, with 782 million people estimated to be connected online during that period [2]. Recently, the proliferation of mobile phone BSs had increased concerns from the public about the possible risks of radio frequency radiation in the coming years, especially when 5G infrastructure deployment begins [3,4]. RF-EMF exposure has been a critical topic for telecommunication organization to retain safety in the recent decade, therefore many researchers have explored in former wireless network generations in 2G, 3G, and 4G technology with exposure emitted from BS and MP whether involve in Electromagnetic Hypersensitivity (EHS) or Non-EHS adults are on the physiological (blood pressure, body temperature or heart rate) changes, cognitive performance [5–13], subjective symptoms [5,10,14–18] and EMF perception [15,16]. These are the few relevant papers conducted assessment and reported the effects of RF-EMF radiation primarily focused on BS and MP.

The field of computer science known as Machine Learning (ML) has the potential to revolutionize the study of epidemiology [19]. Before using any ML approach, normalizing the data is the first step. This is done for the hybridized Multi-Stage Feature Selection (MSFS) classification for the health effect detection of Malaysian adults' exposure to 5G base station antenna data. There are 60 persons that participated in the study. They are subjected to a number of counterbalanced, randomized, and double-blind situations during the study that replicate emissions from 5G base stations. The proposed parameters' normalization approach has a significant impact on the model's performance [20,21]. Numerous studies have demonstrated the value of data normalization for various data sets in ensuring the correctness of model findings by Shahriyari [21] and Raju *et al.,* [22]. Data normalization is seen to be extremely important during the data pre-processing stage since it increases the prediction accuracy [22]. If the data contain significant levels of inconsistency and difficulties with magnitude mismatch, hybrid normalization may be utilized, which entails using two or more normalizing algorithms [23]. Dynamic normalizing method selection refers to the process, whereas static normalization technique selection refers to the process where the technique is fixed for all classification tasks. If the data complexity is large, dynamic normalizing technique selection depending on the data properties can be used [20]. To investigate the impact of adequate normalization on model prediction accuracy, researchers utilized the two most widely used normalization strategies, min-max and z-score. By referring to Liang *et al.,* [24], the two data sets used in gene expression data analysis were normalized by scaling to 0–1. In [21], three normalization techniques have been used which are scaling, vector normalization and z-score to discover the gene expression that predicts the survival in patients with colon tumor. In [25], the authors used four normalization techniques: histogram normalization, generalized scale normalization, generalized ball-scale normalization and custom normalization to check the impact on the accuracy of radiomic ML models. Andrew *et al.,* [26] used five normalization techniques: Logarithmic Sum Squared Voltage value (RLSSV), Relative Logarithmic Voltage value (RLV), Relative Sum Squared Voltage (RSSV), Relative Voltage value (RV), and Fractional Voltage Change value (FVC) to build a classifier for early fire detection [26]. In [27], the authors used the five normalization techniques implemented in [26] and another four normalization techniques which were Decimal Scaling (DS), Z-score (ZS), Min-Max (MM) and Mean & Standard Deviation (MSD) for early breast cancer size prediction. However, to the best of our knowledge, no studies regarding ML was utilized for the dataset involved on the hybridized MSFS selection classification for 5G BS antenna health effect detection without considering the hybrid dataset of employing ML approaches for prediction models and feature selection techniques using data from weak radiofrequency radiation effect on human.

2. Methodology

The cognitive, physiological, EMF perception, and VAS parameters outcomes are attained from 60 subjects (30 EHS and 30 Non-EHS) who participate in the experiment and have completed all four 5G base station signal exposures. For each normalization method which are Z Score Normalization (z score), Linear Scaling (LS), Binary Normalization (BNN), Bipolar Normalization (BPN), Min-Max Scaling (MMS), t Score Normalization (t score), Decimal Inverse Logarithmic Scaled Normalization (DILSN), Relative Mean Normalization (RMN), Relative Standard Deviation Normalization (RSDN), Robust Normalization (RN), Variation Normalization (VN) and Relative Interquartile Normalization (RIN) enhanced ML pre-processing accuracy. The main framework of the research is shown in Figure 1.

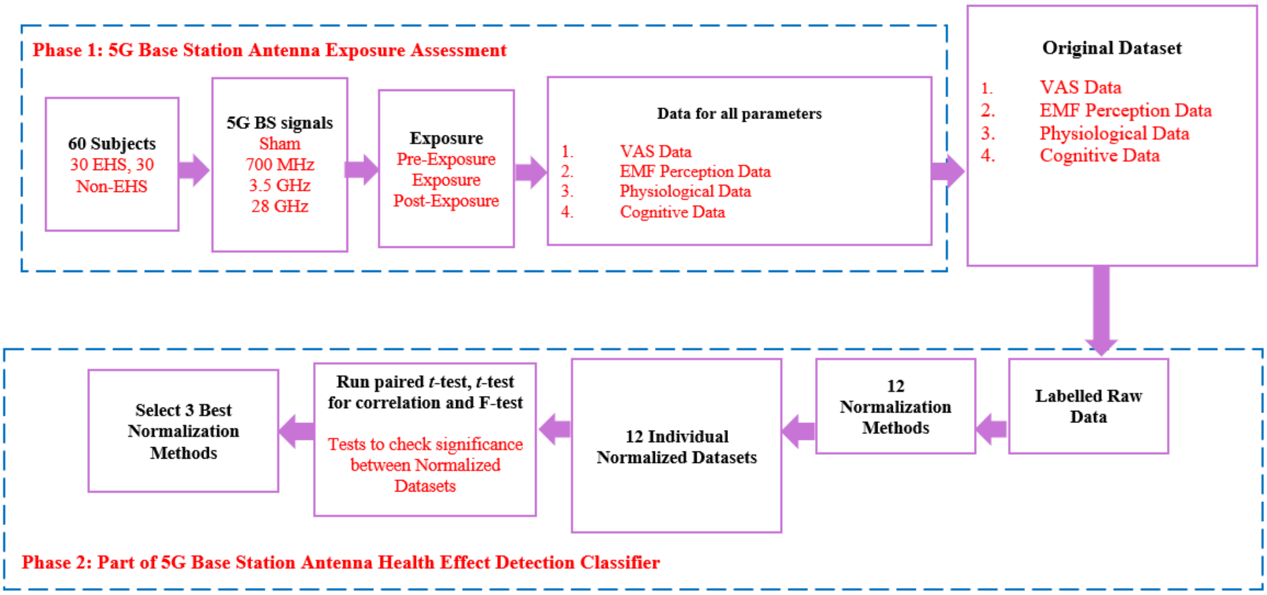

Fig. 1. The research methodology of the normalization methods design of the hybridized MSFS 5G BS antenna health effect detection based on the physiological parameters, cognitive performance, VAS parameter and EMF perception ability of adults.

Each proposed method was run across all datasets of the proposed parameter using ML methods in MATLAB in order to computing the p-value and F-value in the ML first stage design the hybridized MSFS and hybrid feature for 5G BS antenna health effect detection based on the physiological parameters, cognitive performance, VAS parameter and EMF perception ability of adults.

i. z score: Z Score Normalization Method equation, where x is the data input, μ is the mean data and σ is the standard deviation of the data.

$$x' = \frac{x-\mu}{\sigma} \tag{1}$$

ii. LS: Linear Scaling Normalization Method equation, where x is the data input, min is the minimum data and max is the maximum data.

$$x' = \frac{(x-min)}{max - min} \tag{2}$$

iii. BNN: Binary Normalization Method equation, where x is the data input, min is the minimum data and max is the maximum data.

$$x' = \frac{0.8\ (x-min)}{max - min} + 0.1 \tag{3}$$

iv. RMN: Relative Mean Normalization Method equation, where x is the data input and μ is the mean of the data.

$$x' = \frac{x}{\mu} \tag{4}$$

v. RSDN: Relative Standard Deviation Normalization Method equation, where x is the data input and σ is the standard deviation of the data.

$$x' = \frac{x}{\sigma} \tag{5}$$

vi. RIN: Relative Interquartile Normalization Method equation, where x is the data input and IQR is interquartile range of the data.

$$x' = \frac{x}{IQR} \tag{6}$$

vii. BPN: Bipolar Normalization Method equation, where x is the data input, min is the minimum data and max is the maximum data.

$$x' = \frac{1.8\ (x-min)}{max - min} - 0.9 \tag{7}$$

viii. MMS: Min-Max Normalization Method equation, where x is the data input, min is the minimum data and max is the maximum data.

$$x' = \frac{x}{max - min} \tag{8}$$

ix. t score: t - Score Normalization Method equation, where x is the data input, μ is the mean data, n is the number of total sample data and σ is the standard deviation of the data.

$$x' = \frac{x-\mu}{\frac{\sigma}{\sqrt{n}}} \tag{9}$$

x. DILSN: Decimal Inverse Logarithmic Scaled Normalization Method equation, where x is the data input.

$$x' = 10^{-12} 10^{0.1x} * 10^{7} \tag{10}$$

xi. RN: Robust Normalization equation, where x is the data input, and IQR is the interquartile range.

$$x' = (x - median)/IQR \tag{11}$$

xii. VN: Variation Normalization equation, where x is the data input, σ is the standard deviation of the data and μ is the mean data.

$$C_{v,i} = \frac{\sigma}{\mu}\, x_i \tag{12}$$

3. Results

In order to compute the p-value and F-value for each parameter and ensure that the three best normalization methods will be selected for the design of stage two of hybridized MSFS by feature extraction method, feature selection, and feature fusion which are very reliable for ML scope. The analysis is conducted to determine which normalization method should be used after the pre-processing stage in ML. The analysis is on selection of normalization method conducted using statistical computations of statistical *p*-value and *F*-value. From the 12 data set matric, the three data matric which pass the selection criteria of having *p*-value less than 0.05 and highest *F*-value are selected. Statistical calculations of the statistical p-value and F-value are used in the analysis to choose the normalization procedure [27]. The three data matrices that meet the selection criterion of having a p-value less than 0.05 and the greatest F-value are chosen from the 12 data set matrices.

In each table, the term "Group" refers to both the Non-EHS (Electromagnetic Hypersensitive) individuals and the EHS subjects, who made up the data. Each participant had three exposure stages throughout each session: Pre-Exposure, Exposure, and Post-Exposure. The "Signal" refers to four kinds of 5G base station exposure: Sham (No Exposure), 5G 700 MHz, 5G 3.5 GHz, and 5G 28 GHz. Cognitive parameter (Backward Digit Span Task, Flanker Task, Tower of London Task), physiological parameter (Body Temperature, Systolic Blood Pressure, Diastolic Blood Pressure, and Pulse), VAS parameter (Anxiety, Arousal, Fatigue, Tension, Relaxation, and Discomfort), and EMF perception parameter are the four proposed parameters that are included 5G Base Station Condition and 5G Signal emitted based on the results of the two studies performed utilizing statistical calculations of the p-value and F-value. The suggested normalization techniques account for three out of the total number of data retrieved when the F-values and p-values for each reading of the normalization method are compared.

Based on Table 1, data matrices of BNN for physiological parameter which measured during exposure for Diastolic Blood Pressure part have the most numbered selection characteristic which from its F-value of subject group and 5G base station signal emitted, while p-value less than 0.05 showed also for BNN and BPB for its group category and as similar to the statistical analysis for Table 2, physiological parameter of Pulse during after exposure when F-value and p-value obtained from it is based on the criteria selection for data matric RSDN. Table 3 contained the VAS parameter dataset for Diastolic Blood Pressure during and after exposure and the data matric of BNN for Subject category and 5G signal selection emitted but not for the p-value of Signal analysis. Table 4 contains the normalization technique data matrices BPN for the post-exposure measured on the Tension parameter from VAS scope. BNN, MMS, and RSDN are the three best normalization approaches selected based on the selection criteria from the overall data parameter experiment, and these will be used for further analysis in the hybridized MSFS for the short-term 5G base station exposure antenna on the health effect.

Table 1
Statistical analyses of the 12 normalization methods for the Physiological parameter for Diastolic Blood Pressure (Exposure) dataset

		DIASTOLIC BLOOD PRESSURE (Exposure)											
		z score	LS	BNN	BPN	MMS	t score	DILSN	RIN	RMN	RSDN	RN	VN
F-value	Group	0.038	2.026	6.171	5.742	0.409	0.548	0.049	-	0.010	2.741	0.209	-
	Signal	0.021	0.832	1.122	0.135	2.000	1.198	0.125	-	0.635	0.341	0.625	-
p-value	Group	0.847	0.156	0.014	0.017	0.523	0.460	0.825	-	0.919	0.099	0.648	-
	Signal	0.996	0.478	0.341	0.939	0.115	0.311	0.945	-	0.593	0.795	0.600	-

Table 2
Statistical analyses of the 12 normalization methods for the Physiological parameter for Pulse (Exposure) dataset

		PULSE (Exposure)											
		z score	LS	BNN	BPN	MMS	t score	DILSN	RIN	RMN	RSDN	RN	VN
F-value	Group	1.461	3.109	3.186	0.005	4.678	0	0.154	-	0.152	4.129	0.788	1.461
	Signal	0.010	0.350	0.159	0.641	0.295	1.298	0.659	-	0.170	1.956	2.054	0.010
p-value	Group	0.228	0.079	0.076	0.943	0.032	0.996	0.695	-	0.697	0.043	0.375	0.228
	Signal	0.999	0.789	0.924	0.590	0.829	0.276	0.578	-	0.917	0.121	0.107	0.999

Table 3
Statistical analyses of the 12 normalization methods for the Physiological parameter for Diastolic Blood Pressure (Post-Exposure) dataset

		DIASTOLIC BLOOD PRESSURE (Post-Exposure)											
		z score	LS	BNN	BPN	MMS	t score	DILSN	RIN	RMN	RSDN	RN	VN
F-value	Group	0.000	1.888	6.779	6.663	0.664	0.084	0.013	-	0.003	2.968	0.001	0.000
	Signal	0.081	0.449	0.512	0.180	1.955	0.333	0.333	-	0.391	0.279	0.438	0.081
p-value	Group	0.984	0.171	0.010	0.010	0.416	0.772	0.909	-	0.960	0.086	0.974	0.984
	Signal	0.970	0.718	0.674	0.910	0.121	0.802	0.801	-	0.760	0.841	0.726	0.970

Table 4
Statistical analyses of the 12 normalization methods for the VAS parameter for Tension (Post-Exposure) dataset

		TENSION (Post-Exposure)											
		z score	LS	BNN	BPN	MMS	t score	DILSN	RIN	RMN	RSDN	RN	VN
F-value	Group	2.358	0.146	0.585	2.358	1.321	2.358	1.321	1.321	1.227	0	-	-
	Signal	0.632	0.436	1.424	2.130	2.953	2.130	0.436	0.436	0.318	0.242	-	-
p-value	Group	0.126	0.703	0.445	0.126	0.252	0.126	0.252	0.252	0.297	1.000	-	-
	Signal	0.595	0.727	0.236	0.097	0.033	0.097	0.727	0.727	0.812	0.867	-	-

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