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Unraveling Body Vitals as Traumatic Event-Caused Stress Indicators

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***Abstract*—Exploration and analysis of changes in human biometrics, such as heart rate and blood pressure associated with exposure to traumatic events is the primary goal of this article. We aimed at answering the questions on whether there is a significant difference in biometrics observed in the peaceful and disaster times. Overall, we developed and tested a new technique to measure the difference in the indicators of stress during relatively peaceful times, and during natural and human-made disasters and crises. The proposed approach holds significant potential in the context of e-health and mass migration, offering a valuable tool to recognize and address stress in traumatic events resulting from, for example, forced displacement, armed conflicts, and the impacts of climate change.**

***Index Terms*—heart rate variability, blood pressure, pulse, stress detection, wearable devices, linear regression, statistics.**

I. Introduction

The phenomenon of global climate change, coupled with its consequential effects such as epidemics, war conflicts, and substantial population migrations, engenders a marked escalation in the incidence of stress-inducing circumstances. The physiological impact of stress on the human body can lead to pathological alterations, unless proactive measures are implemented to mitigate these consequences. As such, there emerges a compelling imperative to promptly undertake the diagnosis of stress-related conditions.

Stress has become increasingly pervasive in modern society. It has been linked to numerous physical and mental health problems. Understanding and effectively monitoring of stress levels is crucial for timely intervention and support. In recent years, the usage of body biometrics, or vitals, as stress indicators, was considered instrumental for unraveling the complex relationship between physiological responses and mental well-being [1].

Measuring the body vitals are performed using wearable devices such as smartwatches and fitness trackers. They can continuously monitor heart rate (HR) and blood pressure (BP), providing real-time data for individuals and healthcare professionals.

This study is motivated by the urgent need to assess individuals' stress using body biometrics as indicators. We aim to develop an approach to link environmental stressors such as traumatic events to the changes in the body vitals captured using wearable devices. It is well-known that even seemingly minor stressors can adversely affect HR and BP, potentially contributing to burnout, anxiety, and other negative psychological consequences. Note that there is a difference between stress and physiological workload. If both HR and BP are elevated, it may be indicative of stress. In contrast, if only one type of measurement is high (e.g., elevated HR without a corresponding increase in BP), it may suggest a response to physiological workload, like exercise or physical exertion.

While previous studies have explored the relationship between cognitive workload (such as solving mathematical problems) or physical workload (such as running exercise) and physiological responses [2], [3], this research focuses on the impact of traumatic events such as wartime events, on stress levels. To capture the causal relationships between psychological and physiological well-being during times of significant stress, we analyze the vital data using machine learning.

II. Problem formulation and related works

The relationship between HR and BP during stressful situations is multi-factorial and is subject to variability depending on the stressors and individual characteristics. It is known that human sympathetic nervous system is activated in response to a stressor, increasing HR and BP. This increase in HR is mediated by the release of adrenaline and noradrenaline, which stimulate the heart to contract more forcefully and rapidly. The increase in BP is due to the constriction of blood vessels, leading to increased vascular resistance [4].

The relationship between HR and BP can vary depending on the stressor's type, intensity, and duration, the individual's age, fitness level, and underlying health conditions. For instance, HR and BP can increase in response to acute stressors like exercise or a sudden threat. In contrast, in response to chronic stressors like job stress or financial worries [5], HR may increase while BP remains elevated for longer.

The authors of [6] studied bidirectional interactions between BP and HR. Traditional methods neglect HR's effect on BP. Sixteen volunteers underwent noninvasive methods to record signals. The authors analyzed causality using time-

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domain, frequency-domain, and information-domain analysis. Results showed changes in causal coupling from SBP to RR across conditions, indicating that nonlinear interaction mechanisms play a role in cardiovascular control during mental stress.

The effect of stress on heart function is primarily observed in the HR [7]. Depending on the direction of the sympathovagal response shift, the HR may increase or decrease [8]. Another significant effect of stress on cardiovascular function is BP [9]. Stress triggers the autonomic sympathetic nervous system, leading to increased vasoconstriction. It, in turn, can result in elevated BP, increased blood lipids, disorders in blood clotting, vascular changes, atherogenesis, and ultimately cardiac arrhythmias and myocardial infarction [10]. These stress-induced effects are clinically observed in cases of atherosclerosis and can lead to an increase in coronary vasoconstriction.

III. Methods

The study focuses on unraveling the relationship between the stress caused by the traumatic events of wartime and the human body vitals measured on subjects before and after the onset of war in Ukraine in February 2022. The body vitals, or biometrics, included HR, systolic and diastolic pressure (SBP and DBP), and their derivative such as pulse pressure (PP) which is mathematically defined as the subtraction of the DBP from SBP. These measurements were acquired through a wearable device known as a Holter placed on the subject's chest, allowing for continuous cardiovascular parameter monitoring during both the daytime and nighttime.

The study hypothesis was formulated as follows: "Is there a significant difference in human vitals such as HR, SBP, DBP and PP observed in peace time (pre-war) and war times? " The wartime events, being overall traumatic and negatively affecting mental health, were considered an external stressor.

The methodology to test this hypothesis includes:

1) Data gathering from wearable devices.
2) Evaluation of main statistics for subjects' group comparison.
3) Detection of outliers and their deletion from the dataset.
4) Construction of linear regression models to establish interrelationships among various cardiovascular indicators.
5) Classification using the average-minimum and average-maximum method.
6) Assessment of statistical significance using the Mann-Whitney test to corroborate the proposed hypothesis.

We distinguish the mental, or emotional stress caused by external stressors and the stress caused by physical or cognitive (like solving problems) activities. These stressors cause the cardiovascular system reaction. The logic underlying the formulated hypothesis, in terms of those changes that are indicated by changes in vitals, is shown in Figure 1. When a person is prone to stress, not accompanied by high physical activity, the body's global oxygen debt increases sightly or practically does not change. At the same time, blood flow through arteriovenous shunts increases, causing a notable elevation in BP. With concomitant physical activity, an increase in nutritious blood flow through the capillary exchange system, while the detected increase in BP may be less pronounced.

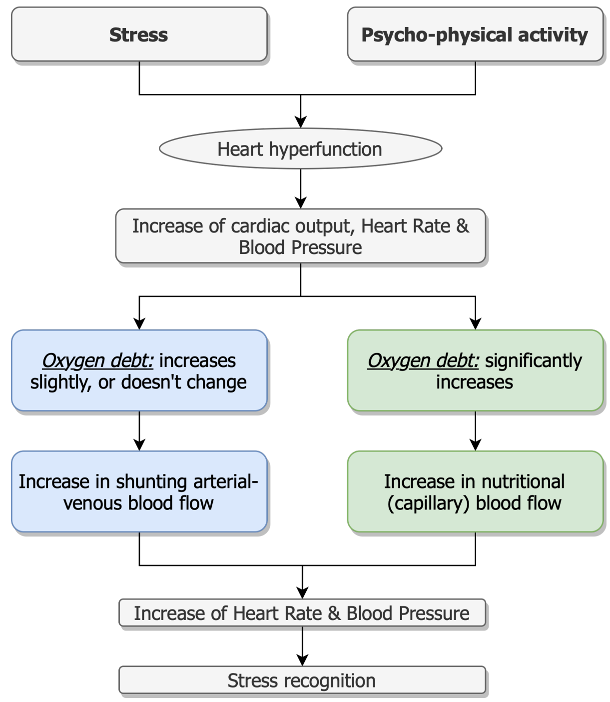


Fig. 1. The diagram that represents the algorithm and approach to unravelling body vitals

A. Data

This study employed a data collection methodology involving the participation of individuals who were invited to "Dobre Sertse" Medical Center, located in Kyiv, Ukraine. The research involved daily monitoring of a cohort comprising 33 individuals. The apparatus utilized for this process was the ABpro Holter system, which adheres to the standards of the European Society of Hypertension [11]. This system continuously recorded SBP, DBP, and HR over 24 hours. In addition, PP was calculated, mathematically expressed as the difference between SBP and DBP. It takes measurements at 15-minute intervals during the day and extends to 30-minute intervals at night, explicitly targeting sleeping hours.

The gathered data were processed to create a comprehensive database, containing 2391 instances, averaging around 73 per participant. This approach enabled the exploration of stress-related physiological changes in individuals, providing insights into the potential impact of stressors on cardiovascular health.

Before the outbreak of the full-scale war in Ukraine on February 24, 2022, Holter monitoring was executed on a sample of 17 patients during the period extending from December 15, 2017, to February 22, 2022. Following the inception of military conflicts, 16 patients were monitored between April 29, 2022, and May 25, 2023. Of the 33 patients, 19 were identified as male and 14 as female. Among the aggregate of 2391 recorded observations, only nine were conducted unscheduled, with 8 of these coinciding with the period after the commencement of the war. Moreover, of the 1109 observations registered post-war initiation, 52 occurred during airstrike alert instances.

In the context of wartime-related stress, emotional stress can manifest spontaneously at daytime, irrespective of an individual's prevailing emotional disposition. During nighttime hours, it may be precipitated by factors such as air raid alerts, missile attacks, aerial defense engagements, and other related events.

B. Statistical observation of data

This analytical component aimed to compare physiological variables, specifically SBP, DBP, PP, and HR, across distinct population cohorts, emphasizing pre-war and post-war observations. The statistical hypotheses were formulated as follows:

- H_0 (null hypothesis): the difference in physiological variables between pre-war and post-war observations is insignificant ($p \geq 0.05$).
- H_1 (alternative hypothesis): the difference in physiological variables between pre-war and post-war observations is significant ($p < 0.05$).

First, the normality of the distribution for SBP, DBP, PP, and HR was appraised using the Shapiro-Wilk test [12], [13]. The results revealed a deviation from the Gaussian distribution, indicating non-normality ($p < 0.05$). As a result of this finding, non-parametric statistical methods were adopted for subsequent analysis.

The daytime data analysis used instances harvested at 15-minute increments during daylight hours. The statistical characteristics of this dataset, comprising the mean (μ), the minimum (Min), first quartile ($Q1$), median ($Q2$), third quartile ($Q3$), and maximum (Max) values [14], are systematically cataloged in Table I. These statistical measures are presented for two distinct observational cohorts: before (993 observations) and after (858 observations) the invasion periods.

TABLE I
STATISTICAL SUMMARY OF DAYTIME OBSERVATIONAL COHORTS BEFORE (B) AND DURING (D) THE WAR TIME

Index		μ	Min	$Q1$	$Q2$	$Q3$	Max
SBP	B	126.39	70.00	116.00	125.00	138.00	185.00
	D	126.53	59.00	115.75	124.00	136.00	194.00
DBP	B	**75.42**	26.00	65.00	**75.00**	85.00	145.00
	D	**78.57**	22.00	69.00	**78.00**	88.00	133.00
PP	B	**50.97**	15.00	39.00	**50.00**	61.00	107.00
	D	**47.96**	15.00	38.00	**47.00**	57.00	116.00
HR	B	**80.59**	44.00	68.00	**77.00**	91.00	185.00
	D	**84.16**	47.00	70.00	**81.00**	95.00	240.00

The nonparametric Mann-Whitney U test [15], deemed suitable given the comparison of two distinct groups and the non-normal distribution of data, was employed in congruence with the given hypotheses. Upon application of this test, it was found that the null hypothesis was validated in the case involving SBP ($p = 0.465$), implying that the before and after the outbreak of war cohorts exhibit no significant differential in this specific measure.

Conversely, concerning DBP ($p < 0.05$), PP ($p < 0.05$), and HR ($p < 0.05$), the alternative hypothesis was upheld. This validation is corroborated by the data presented in Table I, which indicates a significant discrepancy among all statistical measures for described indexes. We highlight in bold type the main characteristics of the groups which are the median and the mean. This approach was also applied to other results in Tables II and V. In the nighttime, the data is exclusively collected during nocturnal hours at half-hour intervals. The same statistical measures applied to the daytime data were computed for the before (consisting of 289 observations) and after (comprising 251 observations) the outbreak of war cohorts. Table II compiles the corresponding statistical outcomes.

TABLE II
STATISTICAL SUMMARY OF NIGHTTIME OBSERVATIONAL COHORTS BEFORE (B) AND DURING (D) THE WAR TIME

Index		μ	Min	$Q1$	$Q2$	$Q3$	Max
SBP	B	112.17	74.00	102.50	111.00	121.00	160.00
	D	115.41	43.00	100.00	115.00	129.00	181.00
DBP	B	**60.45**	36.00	53.00	**60.00**	67.00	109.00
	D	**67.00**	22.00	56.00	**66.00**	75.00	118.00
PP	B	**51.72**	25.00	43.00	**50.00**	60.00	91.00
	D	**48.41**	15.00	40.00	**48.00**	57.00	89.00
HR	B	**65.40**	39.00	57.00	**66.00**	74.00	120.00
	D	**71.22**	46.00	56.00	**69.00**	82.00	208.00

Concurrent with the findings from the daily data, the Mann-Whitney U test revealed a significant difference between the two cohorts in terms of DBP ($p < 0.05$), PP ($p < 0.05$), and HR ($p < 0.05$). These disparities are further substantiated by the statistical insights elucidated in Table II. In addition, no statistically significant differences were observed in the measures of SBP ($p = 0.053$) between the two cohorts.

C. Regression Analysis and Unsupervised Learning

To evaluate the performance of the linear regression algorithms, we utilized a dataset containing HR and BP measurements from a diverse group of individuals exposed to varying environmental conditions. First, we employed OLS [16], a linear regression algorithm that assumes a linear relationship between the independent and dependent variables. Subsequently, we explored two robust algorithms, RANSAC [17] and Theil-Sen [18], which are less sensitive to outliers and can accurately estimate the underlying trends in the presence of noise or extreme observations.

We compared the R-squared values [19] obtained from analyzing a specific patient's data. R-squared is a statistical measure that quantifies the proportion of the variance in the dependent variable explained by the independent variables. It helps identify the algorithm that offers the highest predictive power and accurately captures the underlying relationships between HR, BP, and stressors. The analysis of R-squared values revealed valuable insights regarding the performance of the linear regression algorithms. OLS [16] and Theil-Sen [18] showed excellent performance. However, RANSAC [17] provided greater accuracy, thus, a decision was made to use it for further calculations. Graphically in Figure 2, the comparison results are shown.

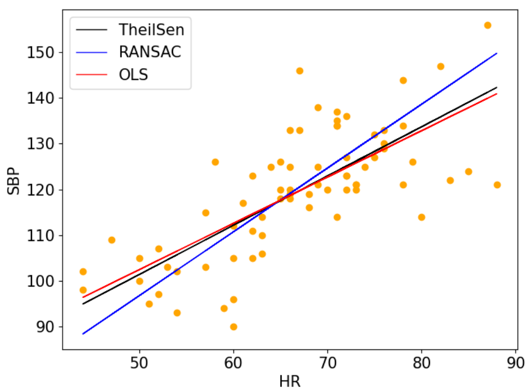


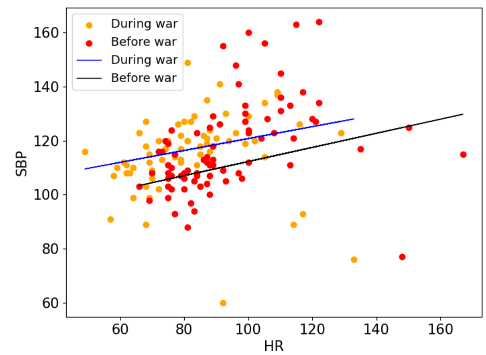
Fig. 2. Comparison of Linear Regression methods: Theil-Sen (black), RANSAC (blue), OLS (red) on the example of HR vs. SBP.

We evaluated linear regression in two distinct groups: the pre-war group and the during-war group, subsequently stratifying them based on gender.

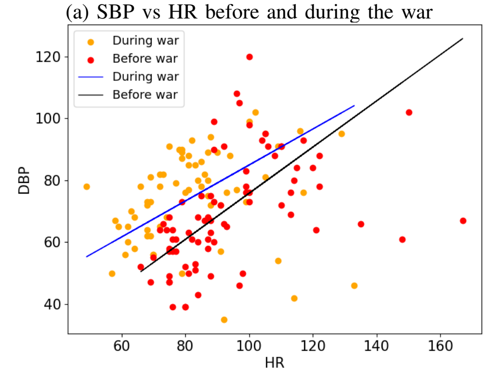
Initially, we normalized our dataset and applied the algorithm to analyze two groups, further stratified by gender. The outcomes of this analysis did not yield statistically significant results. Therefore, we applied the algorithm individually for each patient, followed by a comparison within the previously described division into two distinct groups. Figure 3 shows an example of the constructed regression for HR vs SBP (Figure 3a) and HR vs DBP (Figure 3b). In the graphs for the pre-war period, we observed a moderate positive correlation between HR and SBP as well as HR and DBP, indicating that as HR increased, SBP and DBP tended to increase as well. Interestingly, there are distinct changes in the HR-vascular parameter relationships. The correlation between HR and SBP appeared stronger, suggesting an intensified cardiovascular stress response. Additionally, the correlation between HR and DBP seemed relatively similar compared to the pre-war period.

Note that the dataset encompasses observations from both daytime and nighttime, thus, we analyze these observations collectively without considering them as a time series. The significance lies in the availability of the data rather than the specific intervals or time points. After constructing regression lines for each patient, we computed various metrics of linear regression, including root mean squared error (RMSE), coefficient of determination r^2 score, and mean absolute percentage error (MAPE). The results are shown in Table III.

The normality of the data distribution within these patient model metrics was assessed using the Shapiro-Wilk criterion. The resulting data demonstrated that, with a significance level of $p \geq 0.05$, the RMSE associated with the SBP, DBP, and PP models conformed to a Gaussian distribution. Conversely, in all other instances, the alternative hypothesis was validated ($p < 0.05$), thus indicating a non-normal distribution of the data.



(a) SBP vs HR before and during the war



(b) DBP vs HR before and during the war

Fig. 3. Illustration of the Linear Regression analysis for one subject before and during the war for (a) SBP vs HR and (b) DBP vs HR.

TABLE III
LINEAR REGRESSION METRICS BASED ON DEPENDENCY BUILDING RESULT BETWEEN HR AND SBP, DBP, PP

Index	Gender		RMSE	r^2	MAPE
SBP	Women	Before	4.84	0.28	0.03
		During	4.41	0.19	0.03
	Men	Before	4.81	0.16	0.03
		During	4.37	0.25	0.03
DBP	Women	Before	4.41	0.31	0.05
		During	4.19	0.42	0.05
	Men	Before	4.79	0.22	0.06
		During	3.64	0.27	0.04
PP	Women	Before	3.74	0.15	0.07
		During	3.48	0.15	0.07
	Men	Before	3.76	0.01	0.06
		During	3.94	0.13	0.07

Considering the normal distribution observed in the RMSEs of the SBP, DBP, and PP models, we employed parametric criteria to test statistical hypotheses. In this study, the null hypothesis was formulated as follows: "The RMSEs of SBP, DBP, and PP models for the groups before and after the outbreak of the war exhibit gender-based differences." To assess this hypothesis, the statistical analysis employed Student's t-test [20]. However, for all other instances, the Mann-Whitney test was utilized to evaluate the null hypothesis regarding potential disparities between groups, considering gender. Table IV displays the corresponding p-values for each scenario. It is evident that statistical significance in the DBP model is exclusively observed among males, as evidenced by the regression metrics such as RMSE and MAPE.

TABLE IV
STATISTICAL SIGNIFICANCE OF LINEAR REGRESSION MEASUREMENTS

Index	Gender	Statistical measures		
		RMSE	r^2	MAPE
		p-value	p-value	p-value
SBP	Men	0.47	0.90	0.40
	Women	0.49	0.80	0.53
DBP	Men	**0.01**	0.78	**0.01**
	Women	0.77	0.90	1.00
PP	Men	0.74	0.05	0.45
	Women	0.69	0.90	0.80

To assess the presence of stress, we propose a new approach involving the calculation of average-maximum and average-minimum values. It utilizes the intercept and slope parameters from each model, as well as the corresponding HR values and the variable (DBP, SBP, PP) upon which the regression was based. From the formulated hypothesis and represented algorithm of unraveling body vitals, we undertake a comparison between the average slopes in the groups before and after the onset of the war. If the steepness of these relationships diverge before and after the invasion, it would lead us to infer dissimilarity in the intensity of the BP response and the alterations in HR. These quantities were then incorporated into the following formulae:

$$\text{SBP(HR)} = \frac{\text{SBP}}{\text{HR} \times \text{slope} + \text{intercept}}$$
$$\text{DBP(HR)} = \frac{\text{DBP}}{\text{HR} \times \text{slope} + \text{intercept}}$$
$$\text{PP(HR)} = \frac{\text{PP}}{\text{HR} \times \text{slope} + \text{intercept}}$$

Using the average-minimum and average-maximum observations, we established a definitive criterion: if an observation is determined to possess the average-minimum value across most models, it is assigned a class label of ”0”, indicating the absence of stress. Conversely, if an observation exhibits the average-maximum value across most instances, it is assigned a class label of ”1”, signifying the presence of stress.

For example, we analyzed the first patient’s data, considering HR, SBP, DBP and PP. Linear regression was performed on each variable to obtain the slope and intercept values. For SBP, the slope was 0.22; the intercept was 98.75; for DBP: 0.52 and 26.78; for PP: -0.16 and 48.20, respectively. Using the values above, we calculated that SPB(HR) = 1.10, DBP(HR) = 1.14, PP(HR) = 1.26.

By applying these values to the respective formula, we determined the class of distribution for each variable. Notably, all values obtained were greater than 1, indicating that they fall into the average-maximum class, signifying the presence of stress.

For the research hypothesis validation, a comparative analysis was conducted between the observation groups’ four primary indicators (SBP, DBP, PP, HR), classified based on hypothetical class labels. The statistical technique employed for this purpose was the Mann-Whitney test. The test results revealed a significant difference ($p < 0.05$) between the groups across all four indicators in all statistical measures, thus leading to the acceptance of the alternative hypothesis. These findings are further supported by Table V, which clearly illustrates substantial BP variation among the observation groups while displaying relatively insignificant discrepancies in HR values.

TABLE V
COMPARISON OF STATISTICAL MEASUREMENTS FOR “STRESS (S)” AND “NO STRESS (N)” CLASSES (CL)

Index	CL	Statistical measures					
		μ	Min	$Q1$	$Q2$	$Q3$	Max
SBP	N	**118.23**	74.00	109.25	**118.50**	126.00	159.00
	S	**129.37**	94.00	121.00	**128.00**	138.00	185.00
DBP	N	**70.76**	41.00	62.00	**70.00**	78.00	104.00
	S	**77.08**	45.00	68.00	**77.00**	84.00	121.00
PP	N	**47.47**	16.00	38.25	**46.00**	56.00	84.00
	S	**52.29**	21.00	42.00	**51.00**	64.00	99.00
HR	N	**75.11**	39.00	63.00	**74.00**	84.00	191.00
	S	**77.07**	44.00	65.00	**74.00**	88.00	196.00

Henceforth, the approach used to ascertain the average-maximum and average-minimum values of the regression model provides a means to classify the data, even without prior knowledge regarding stress at any given time. This proposition finds additional reinforcement in the observation that, on average, the ”stress” group exhibits significantly elevated BP levels compared to the ”no stress” group, accompanied by marginally higher HR values.

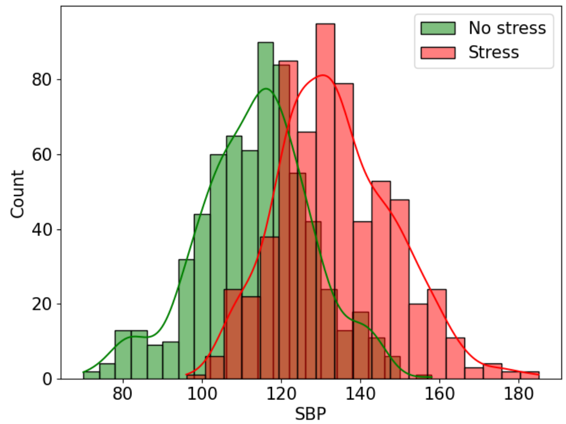
In order to visually trace the statistically significant difference between the groups, the distribution for ”Stress”/”No stress” classes before the war is shown in the Fig. 4a and distribution for ”Stress”/”No stress” classes during the war is shown in the Fig. 4b.

IV. CONCLUSION AND FUTURE WORK

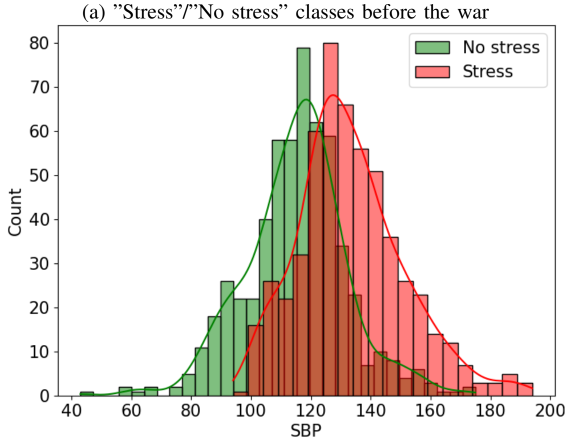
The study offered an in-depth analysis of cardiovascular measurements obtained from patients in the presence of the external stressor such as a full-scale war. We aimed at answering the questions on whether there is a significant difference in physiological indicators such as HR and BP observed in pre-war and war times. This hypothesis provided a guiding framework, statistical analysis, constructing regression models to establish interrelationships among various cardiovascular indicators, and adopting a novel approach that employed average-maximum and average minimum values to classify observations effectively.

Emotional stress in wartime is a complex phenomenon that can manifest spontaneously during air raid alerts, aerial defense engagements and other wartime events at any time of day or night.

The results unveiled noteworthy differences in the values of DBP, PP, and HR between the two groups of subjects (pre-war and war time). Furthermore, the statistical significance to corroborate the proposed hypothesis was assessed. After comparing three different approaches, it was observed that the RANSAC method yielded superior results, as indicated by a higher R-squared value. Consequently, this method was employed for each patient, subsequently facilitating the



(a) "Stress"/"No stress" classes before the war



(b) "Stress"/"No stress" classes during the war

Fig. 4. Illustration of the data distribution among Stress/No stress classes before and during the war.

calculation of linear regression metrics. Nevertheless, the results obtained from their analysis failed to exhibit statistical significance for the two groups. It prompted us to adopt an alternative method using average-maximum and average minimum values.

The results of the testing the hypothesis using Mann-Whitney test yield the p-value of less than 0.05, thereby providing compelling evidence to confirm the statistical significance and validate the acceptance of the hypothesis regarding the disparity between the study groups during both the pre-war and war periods. Overall, we developed and tested a new technique to measure the difference in indicators of stress during relatively peaceful times, as opposed to natural and human-made disasters and crises.

In future investigations, we will utilize the advanced machine reasoning that enable predictions of the health status using prior data and additional variables such as demographics and underlying health conditions if such data is available. The new causal models shall enhance the accuracy and efficiency of stress detection in individuals, thereby contributing to developing more effective stress management strategies. The practical value of this study include techniques to improve preparedness of e-health technology to similar disasters, health and migration crises [21].

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