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Developing a Fatigue Detection Model for Hospital Nurses Using HRV Measures and Machine Learning

Wynona Salsabila Hafiz [1], Maya Arlini Puspasari [1,*], Dewi Yunia Fitriani [2,3], Richard Joseph Hanowski [4], Danu Hadi Syaifullah [1] and Salsabila Annisa Arista [1]

[1] Department of Industrial Engineering, Faculty of Engineering, Universitas Indonesia, Depok 16424, Indonesia; wynona.salsabila41@ui.ac.id (W.S.H.); danuhadi@ui.ac.id (D.H.S.); salsabila.annisa04@ui.ac.id (S.A.A.)
[2] Occupational & Environmental Health Research Centre, Indonesian Medical and Education Research Institute (IMERI), Faculty of Medicine, Universitas Indonesia, Central Jakarta 10430, Indonesia; dewi.yunia.fitriani@gmail.com
[3] Department of Community Medicine, Faculty of Medicine, Universitas Indonesia, Central Jakarta 10430, Indonesia
[4] Division of Freight, Transit, and Heavy Vehicle Safety, Virginia Tech Transportation Institute, Blacksburg, VA 24061, USA; rhanowski@vtti.vt.edu
* Correspondence: mayaarlini@ui.ac.id

Abstract: Fatigue among hospital nurses, resulting from demanding workloads and irregular shift schedules, presents significant risks to both healthcare workers and patient safety. This study developed a fatigue detection model using heart-rate variability (HRV) and investigated its relationship with the Swedish Occupational Fatigue Inventory (SOFI) among nurses. Sixty nurses from a hospital in Depok, Indonesia, participated with HRV data collected via Polar H10 monitors before and after shifts alongside SOFI questionnaires. A mixed ANOVA revealed no significant between-subjects differences in HRV across morning, afternoon, and night shifts. However, within-subjects analyses showed pronounced parasympathetic rebound (elevated Mean RR) and sympathetic withdrawal (reduced Mean HR) post-shift, particularly after afternoon and night shifts, contrasting with stable profiles in morning shifts. Correlation analysis showed significant associations between SOFI dimensions, specifically lack of motivation and sleepiness, with HRV measures, indicating autonomic dysfunction and elevated stress levels. Several machine-learning classifiers were used to develop a fatigue detection model and compare their accuracy. The Fine Gaussian Support Vector Machine (SVM) model achieved the highest performance with 81.48% accuracy and an 81% F1 score, outperforming other models. These findings suggest that HRV-based fatigue detection integrated with machine learning provides a promising approach for continuous nurse fatigue monitoring.

Keywords: fatigue detection; heart-rate variability; nurse fatigue; Swedish Occupational Fatigue Inventory; machine learning

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1. Introduction

Fatigue is a mental or physical state that can decrease an individual's ability to complete important tasks safely and effectively [1]. It is regulated by the central nervous system [2], including a sympathetic activation system managed by the sympathetic nervous system, and an inhibitory system controlled by the parasympathetic nervous system [3]. Symptoms of fatigue include drowsiness, dizziness, decreased concentration, reduced alertness, lack of motivation, and decline in both physical and mental performance.

Work-related fatigue is defined as an abnormal feeling of tiredness, exhaustion, lethargy, and loss of drive, which are often associated with stress and depression [4]. Contributing factors include physical and mental tasks that exceed the worker's capacity, workload intensity and duration, reduced quality and quantity of sleep, especially for night shift workers, psychological factors such as interpersonal conflicts, and the worker's health [5].

Current research underscores the critical role of fatigue management in workplace health. The 2023 Work in America Survey highlights mental health as a top priority, with 83% of Millennial employees and 76% of Gen Z workers reporting increased anxiety compared to 2022 [6]. If work-related fatigue is not promptly addressed with adequate rest, it can accumulate over the day, potentially leading to more severe health effects [7]. A 2018 survey by the National Safety Council found that 57% of workers reported absenteeism due to fatigue, 50% had fallen asleep at work, 47% had low productivity, and 32% had been injured or had near-miss incidents due to work fatigue [8]. Moreover, 90% of the companies reported negative impacts of worker fatigue [9]. Consequently, work fatigue is a serious issue that must be addressed as it poses a hazard that can affect worker productivity.

Healthcare services aim to maintain and improve health; prevent and cure diseases; and rehabilitate individuals, groups, and communities. Hospitals play a crucial role in the national healthcare system. As of 2022, there are 3072 hospitals in Indonesia, which is expected to increase in line with a positive trend over the past decade. This highlights the critical role of healthcare workers in ensuring the sustainability of hospital services [10]. Data from the Indonesian Ministry of Health, as reported in the 2022 Indonesia Health Profile, indicate that the healthcare workforce in Indonesia includes approximately 2.02 million individuals, with nurses being the largest group, making up 39.15% of healthcare professionals or 563,739 individuals [11].

Hospitals operate 24 h a day and have high risks associated with occupational health, including fatigue due to shift work [12,13]. Nursing is particularly affected by work-related fatigue caused by shift schedules. According to Shah [14], nurses typically work 8, 10, or 12 shifts. Research on circadian physiology has shown that an 8-h shift is better for the natural body cycle than a 12-h shift. Delving deeper into the shift work literature reveals that the pattern of working nights or rotating shifts, and consequently sleeping less or at suboptimal times, significantly contributes to fatigue [15]. Despite this, 12-h shifts dominate nursing schedules [16,17], and nurses work in various hospital departments such as intensive care units (ICU), emergency rooms (ER), operating rooms (OR), and inpatient wards. ICU nurses care for patients with unstable or critical conditions [18]. ER nurses handle serious illnesses and injuries upon patient arrival at the hospital, often specializing in trauma, cardiac, pediatric, or geriatric care. OR nurses assist with preoperative and postoperative care, ensuring continuity of care during surgical procedures. Inpatient nurses care for patients who are admitted for extended stays.

Nurse performance is crucial to patient treatment outcomes. Fatigue can impair nurses' performance and jeopardize patient safety, making it an issue that must be addressed urgently. The main factors contributing to nursing fatigue were excessive administrative tasks, continuous mental demands, and shift work over long hours. These factors align with the integrative literature review by Alahmadi and Manal [19], which highlighted poor scheduling, overtime, disrupted circadian rhythms, and high stress with low social support as significant contributors to nursing fatigue. Previous studies reveal that shifts exceeding 12 h increase burnout risks, with nurses working $\geq$ 13-h shifts reporting lower patient communication, pain management, and satisfaction [20]. Night shift nurses face significantly poorer sleep quality and elevated chronic fatigue compared to daytime workers [21].

Additionally, fatigue-related impairments extend beyond individual health, increasing errors in care, vehicle accidents, and systemic risks for employers [20].

As frontline healthcare providers, nurses face significant responsibilities, especially with the increasing numbers of patients and workloads [22]. In 2021, the International Council of Nurses (ICN) stated that a global phenomenon of mass trauma has been occurring among nurses since the start of the pandemic [23]. Nurses are constantly exposed to emotionally draining stressors, which increase their risk of occupational burnout and other forms of psychosocial harm [24]. In ICN's recent study [25], more than half (52.4%) of the national nurses' association members (NNAs) indicated that nurses in their country lacked appropriate access to psychological or mental health support in the workplace.

Given the high risk associated with work-related fatigue, it is essential to measure the level of fatigue among nurses. One approach for measuring objective fatigue is heart-rate variability (HRV), which is the fluctuation in the time intervals between adjacent heartbeats [26]. This variability is influenced by the human neuronal system, especially the autonomic nervous system (ANS). The ANS is influenced by the sympathetic nervous system (SNS) and parasympathetic nervous system (PNS). Usually, HRV signals are calculated by analyzing the time interval between the heartbeats using electrocardiography. According to Ni et al. [27], HRV analysis is a commonly used method in fatigue research. An experiment conducted by Li et al. [28] also showed that HRV is an appropriate tool for measuring stress conditions in real working conditions. With advancements in portable, user-friendly heart-rate monitors, HRV has emerged as a valuable tool that simplifies data collection for researchers and enables more accessible fatigue assessment.

The landscape of nursing in Indonesia, as outlined in the World Health Organization Report 2020 [29], highlights critical areas that demand innovative solutions. A significant challenge is the lack of robust regulations concerning working hours and conditions, which can lead to unpredictable and excessive workloads, directly impacting nurse fatigue. There is also a notable absence of rules on minimum wage and social protection for nurses. Moreover, measures are urgently needed to prevent attacks on healthcare workers, ensuring their safety, which could mitigate stress and fatigue. Thus, exploring machine learning for fatigue detection becomes relevant and urgent to address Indonesian nurses' multifaceted challenges.

Previous studies have primarily focused on measuring work-related fatigue levels among nurses. However, as awareness of the need to mitigate risks associated with nurse fatigue grows, there is an increasing demand for a model that can proactively detect fatigue. Machine learning (ML), a specific branch of Artificial Intelligence, enables systems to learn automatically from data [30]. ML is employed to identify patterns in data where the underlying structure is not yet known to predict future data or achieve the desired outcomes [31]. By leveraging both objective data, such as HRV, and subjective data, machine learning can be used to develop a robust nurse fatigue detection model.

Studies have demonstrated the potential of machine-learning algorithms in real-time HRV monitoring for healthcare workers, particularly emergency room nurses [32]. ML algorithms were also proven to assess data and provide accurate cardiac diagnosis for cardiovascular disease patients [33]. Similar models have also been developed for other professions, including drivers [34], athletes [35,36], construction workers [37], and pilots [38]. Despite this progress, machine-learning applications for nurse fatigue detection, particularly in Indonesia, remain underexplored. Given advances in portable and user-friendly HRV monitoring devices [39], research on HRV-based fatigue detection models for nurses is essential. Notably, studies have shown that models trained using selected HRV features can classify physical fatigue with high accuracy [27], and these features also provide critical insights into identifying fatigue states. This study aimed to develop an HRV-based fatigue-detection system using ML specifically designed for nurses. The outcome of this study is to provide a more accurate and effective method for measuring fatigue in healthcare settings. When fatigue can be detected more accurately, hospital management can make appropriate strategies to reduce fatigue among nurses and improve their well-being.

2. Materials and Methods

2.1. Participants

This study employed a cross-sectional design with a purposive sampling method. In this study, the inclusion criteria were working for at least one year as a nurse, serving in one of the working unit departments (ICU/ER/OR/Inpatient), and being healthy individuals. The exclusion criteria for participants were not pregnant and not consuming caffeine, alcohol, or drugs. The participants were first screened to meet the criteria for this study, and the study used a purposive sampling method. We use G*power 3.1 to verify the adequacy of the sample size [40]. The calculation using G*Power with 60 participants generated a statistical power ($1 - \beta$) of 87.3%, which exceeded the suggested minimum statistical power of 80% [41]. This indicated that the sample size in this study was adequate.

2.2. Procedure

This study follows the STROBE Statement as the checklist of items that should be included in reports of cross-sectional studies. The STROBE methodology and data presentation guidelines were available in the Supplementary File. The study was conducted in a hospital with three 8-h working shifts (morning, afternoon, and night). The hospital's occupational health and safety management coordinated the participant recruitment process to maintain organizational protocols. All participants were briefed on the study's purpose, methods, and procedures before signing informed consent and completing demographic questionnaires to ensure all criteria were met before enrollment.

To maintain rigorous data quality and validation, data collection was conducted for all participants before and after their work shift based on their working unit department (ICU/ER/OR/Inpatient). The study protocol required participants to sleep for at least 6 h (within a 24-h cycle) and not to consume caffeine or drugs within 24 h before the start of data collection. Each participant's data were measured before and after their work shift ended to avoid disrupting their workflow too much. Before a shift, participants used HRV for 5 min along with the Polar H10 to monitor their heart rate. After the shift was completed, HRV data were collected again. Once completed, the participants rested for two minutes before completing the SOFI questionnaire. The time taken to complete the SOFI questionnaire was approximately 10 min. Research workflow can be seen in Figure 1.

To control confounding variables in this study, we measured nurses' heart-rate variability and administered the SOFI questionnaire simultaneously in the same period. Their shifts also had the same duration of 8 h, and we monitored their sleep duration to ensure they slept at least 6 h before the data collection. Each participant was given a gold souvenir for their participation in this study.

All participants provided informed consent before participating in the study, and confidentiality of the data was ensured throughout the research process. This study was also conducted following the principles of the Declaration of Helsinki. Ethical approval was obtained from the hospital research ethics committee before the commencement of the research. Written informed consent to publish identifying details was also obtained from all individual participants before their inclusion in the study and has been secured per ethical guidelines. Efforts have been made to anonymize personal information to protect the participants' privacy.

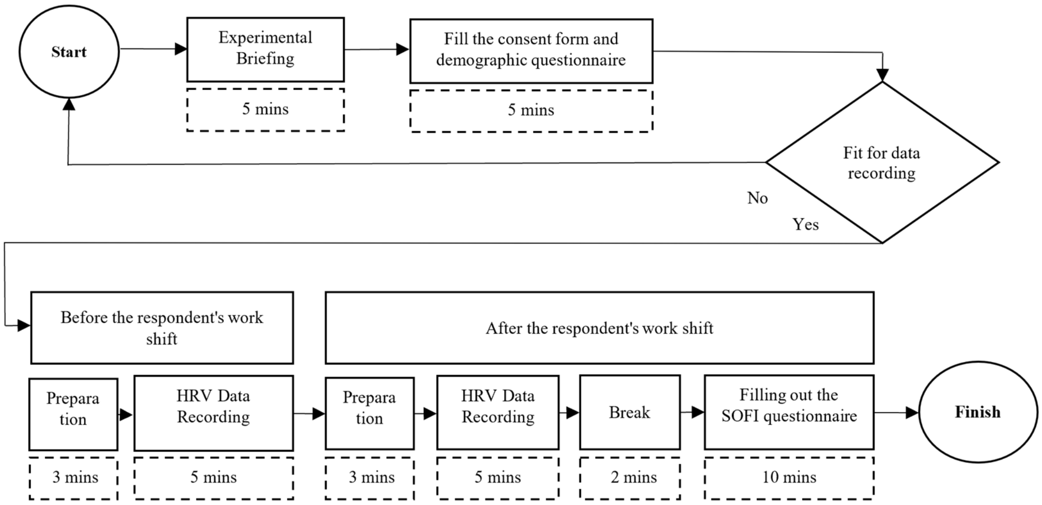

Figure 1. Research workflow.

2.3. Data Recording

2.3.1. Heart-Rate Variability

HRV is the fluctuation of the time interval between adjacent heartbeats [42]. HRV measurements were conducted using a Polar H10 sensor manufactured by Polar Electro Oy in Finland, Elite HRV 5.5.8, and Kubios HRV Scientific 4.1.1. The participants wore the Polar H10 sensor on their chest for 5 min. The Polar H10 sensor, equipped with electrodes on a chest strap, detects the heart's electrical activity using R-waves in an electrocardiogram. The data obtained were a time interval between successive R-waves (RR-intervals), which were then transmitted to a mobile device via Bluetooth. The RR-interval data were recorded using the Elite HRV application, which allows for data recording, storage, and export for further analysis. This application was validated in previous studies to ensure accuracy in capturing the RR-interval signals [26].

The RR-interval data were then analyzed using Kubios HRV Scientific software, specifically designed for scientific research. This software enables comprehensive data processing, including pre-processing to detect and correct noise, correcting misaligned heartbeats, and performing trend removal. After pre-processing, HRV analysis was conducted, generating various time-domain parameters such as Mean RR, SDNN, RMSSD, NN50, and pNN50, as well as frequency-domain parameters such as VLF, LF, HF, and the LF/HF ratio. This combination of tools and applications ensures accurate and in-depth HRV measurements, providing objective insights into the relationship between work fatigue and heart rate in nursing.

2.3.2. Swedish Occupational Fatigue Inventory

In this study, subjective measurements were used to classify the nurses' fatigue and non-fatigue conditions. Subjective measurements of fatigue were assessed using the SOFI. This study used non-fatigue scales from 0 to 3.49 and a fatigue scale from 3.50 to 6.00 [43]. SOFI measured five dimensions of fatigue, represented by 25 items in total, and every item was measured on a Likert scale of 1 to 6.

2.4. Data Analysis

The Shapiro–Wilk test, Mixed ANOVA, and Pearson's R correlation test were used to analyze both objective HRV data and subjective SOFI data. The Shapiro–Wilk test assessed whether the data followed a normal distribution, a prerequisite for parametric statistical analyses. Mixed ANOVA is a statistical technique employed to evaluate mean variations among groups divided into two factors: one factor is classified as a within-subjects factor (repeated measures), while the other is recognized as a between-subjects factor (independent groups). In this study, the within-subjects factor consists of before and after work, and the between-subjects factor consists of 3 shifts (morning, afternoon, and night). Finally, Pearson's R correlation test was conducted to examine the strength and direction of the relationship between HRV data (objective measures) and SOFI data (subjective measures), ensuring alignment between physiological indicators of fatigue and perceived fatigue levels. This comprehensive statistical approach provides insights into the interplay between various factors influencing nurse fatigue.

After performing statistical tests, machine learning designed in Python 3.3 from Jupyter Notebook 6.5.4, with supervised learning, was used to develop the model. Based on Figure 2, the first step of data pre-processing was to adjust for noise and artifacts from the raw data. The second step was to extract key HRV features for analysis. The selected columns were based on heart-rate variability metrics, such as Mean RR, SDNN, Mean HR, RMSSD, NN50, pNN50, LF, HF, and LF/HF. The Swedish Occupational Fatigue Inventory (SOFI) questionnaire was used as the dependent variable to classify the fatigue level of the participants. The SOFI data used included the Total Score, which was categorized into non-fatigue (0–3.49) and fatigue (3.50–6.00) as the cut-off for fatigue labeling [43]. Subsequently, data encoding was performed to transform the data into a more processable format. The final step involved data scaling, in which the variables were normalized using their respective means and standard deviations to ensure consistency across different variables.

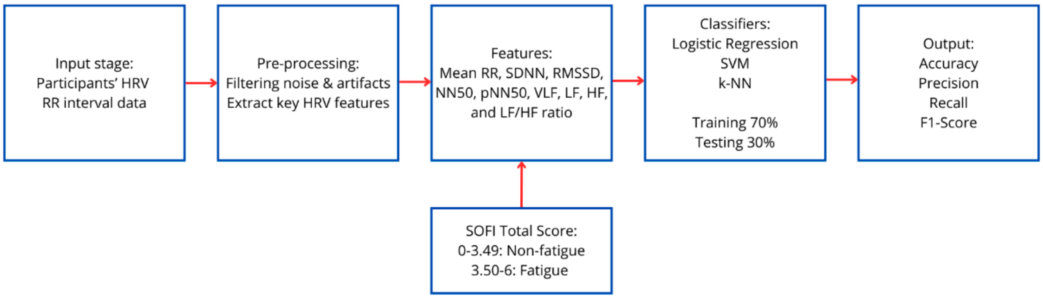

Figure 2. Data classification process.

After this pre-processing, significant features were run through classification, evaluation, and prediction models. Logistic regression, support vector machine (SVM), and k-nearest neighbor (KNN) algorithms were used in this study. A logistic regression model using heart-rate features can predict physical fatigue with good predictions and interpretable parameters for real-life applications in previous research [44]. The SVM algorithm is suitable for complex and small datasets. This makes it a preferred choice in scenarios where data are scarce, such as in specific biomedical applications [45]. SVM algorithms have also been successfully applied to classify the mental and muscle fatigue states [46,47]. The SVM models were also divided into linear, quadratic, cubic, fine Gaussian, and coarse Gaussian-based models to compare further and obtain the highest performance metrics of the model. In addition, k-nearest neighbors (k-NN) can be used to identify the nearest neighbors from one group to a certain point to classify the result. One study utilized the KNN algorithm to identify fatigue after sleeping using a combination of electrocardiogram (ECG), Electromyography (EMG), and electroencephalogram (EEG) parameters [48].

We also conducted a synthetic minority oversampling technique (SMOTE) by adding a copy of the training set because of the imbalanced data to reduce the risk of overfitting. Furthermore, the model's performance was evaluated using accuracy, precision, recall, and F1-score metrics. Accuracy (1) measures the proportion of correctly classified examples out of the total number of examples, including both positive and negative cases. Precision (2) evaluates the proportion of correctly predicted positive cases (true positives) among all cases predicted as positive, reflecting the model's ability to avoid false positives. Recall (sensitivity) (3) assesses the proportion of actual positive cases the model successfully identified as positive, capturing the model's ability to avoid false negatives. Finally, the F1-score (4) provides a harmonic means of precision and recall, offering a balanced measure of the model's ability to predict both positive and negative labels accurately. This ensured a comprehensive evaluation of the model's performance, particularly in datasets with imbalanced class distributions.

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}) \tag{1}$$

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \tag{2}$$

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}) \tag{3}$$

$$\text{F1-Score} = (2 \times \text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall}) \tag{4}$$

3. Results

3.1. Statistical Test

The study included 60 nurses (83.3% female, 16.7% male) from a hospital in Depok, West Java, Indonesia. Participants had a mean age of 28.25 ± 2.18 years and an average working experience of 5.733 ± 1.28 years. HRV parameters, including time-domain and frequency-domain measures, were calculated for all participants following standardized RR-interval data collection and processing procedures. After processing the respondents' RR-interval data, the HRV variables' calculated results were obtained. A summary of HRV data from the collection process is presented in Table 1.

Table 1. Summary of HRV features.

Features	Morning Shift		Afternoon Shift		Night Shift	
	Before	After	Before	After	Before	After
Mean RR	726.71 ± 78.48	739.88 ± 81.52	687.84 ± 71.55	786.32 ± 87.67	721.93 ± 71.74	803.31 ± 86.70
SDNN	29.64 ± 9.53	29.81 ± 9.62	29.89 ± 13.88	35.90 ± 14.26	28.22 ± 9.60	35.38 ± 15.64
Mean HR	83.50 ± 9.21	82.03 ± 9.00	88.18 ± 9.75	77.33 ± 9.90	83.89 ± 8.40	75.54 ± 8.46
RMSSD	28.71 ± 13.41	29.85 ± 12.80	26.62 ± 16.07	35.69 ± 16.80	26.37 ± 10.80	37.27 ± 22.34
NN50	40.13 ± 45.21	41.17 ± 36.89	39.75 ± 55.29	63.45 ± 56.33	30.94 ± 32.04	70.52 ± 73.54
pNN50	10.65 ± 12.40	11.03 ± 10.42	9.68 ± 13.75	17.51 ± 15.67	7.59 ± 7.84	20.39 ± 22.13
VLF	64.62 ± 61.51	58.42 ± 49.04	51.49 ± 40.74	85.40 ± 106.51	63.94 ± 82.84	130.83 ± 165.2
LF	342.44 ± 190.8	316.73 ± 170.0	409.26 ± 333.3	560.49 ± 469.9	346.9 ± 189.29	513.8 ± 362.08
HF	481.62 ± 428.3	501.41 ± 384.07	605.48 ± 705.3	689.04 ± 626.1	392.64 ± 307.1	724.81 ± 819.6
LF/HF	1.07 ± 0.74	0.90 ± 0.57	1.45 ± 1.50	1.32 ± 1.22	1.76 ± 2.05	1.58 ± 1.61

Abbreviations: Mean RR = Mean of RR intervals; SDNN = Standard deviation of the NN intervals; Mean HR, = Mean of heart rate; RMSSD = Root means square of successive NN intervals differences; NN50 = Number of interval differences of successive NN intervals greater than 50 ms; pNN50 = Proportion derived by dividing NN50 by the total number of NN intervals; VLF = Very low frequency; LF = low frequency; HF = High frequency; LF/HF = Low Frequency to High-Frequency ratio.

Subjective data from the SOFI questionnaire were collected using a scale ranging from 0 to 6 for each question. The SOFI data for each question were then averaged within each dimension to calculate the scores for each dimension (Table 2).

Table 2. Summary of SOFI.

Summary	Lack of Energy	Lack of Motivation	Sleepiness	Physical Exertion	Physical Discom-fort	Total Score
n	60	60	60	60	60	60
Mean	4.8	4.6	3.0	2.8	2.8	4.6
St Dev	7.88	7.87	7.92	8.18	8.16	8.18
Min	2.0	1.0	2.0	1.0	1.0	1.0
Max	6.0	5.4	5.8	5.0	5.4	5.5

Abbreviations: n = number of samples; St Dev = standard of deviation; min = minimum value; max = maximum value; Lack of Energy = measure of perceived low energy levels; Lack of Motivation = measure of perceived deficiency in drive or willingness to perform tasks; Sleepiness = measure of the tendency to feel drowsy or have difficulty staying awake; Physical Exertion = measure of the perceived physical strain or effort; Physical Discomfort = measure of perceived physical pain or discomfort; Total Score = aggregate fatigue score (sum of individual subscale scores).

The collected data were tested for normal distribution using the Shapiro–Wilk test, confirming that all data from HRV and SOFI measurements were normally distributed. A mixed ANOVA with a 95% confidence interval was conducted to evaluate the effect of work shifts (morning, afternoon, night) as a between-subjects factor on nurses' HRV variables. The results revealed no significant differences in HRV metrics across the morning, afternoon, and night shifts (Sig. > 0.05). These findings suggest no statistically significant differences in nurses' HRV variables due to the shift type when considering between-subject variation (Table 3).

Table 3. Summary of Mixed ANOVA Tests Between-Subjects Effects.

Measure	df	Mean Square (95% CI)	F	Sig.
Mean RR	2	0.003	0.829	0.442
SDNN	2	0.005	0.088	0.916
Mean HR	2	0.003	0.829	0.442
RMSSD	2	0.002	0.022	0.978
NN50	2	0.019	0.020	0.980
pNN50	2	0.032	0.043	0.958
VLF	2	0.110	0.594	0.555
LF	2	0.082	0.587	0.559
HF	2	0.048	0.116	0.891
LF/HF	2	0.180	0.884	0.419

Abbreviations: df = degrees of freedom; Mean Square (95% CI) = Variance estimate (sum of squares/df) with 95% confidence interval for the mean difference; F = F-statistic (ratio of between-group variance to within-group variance); Sig. = significance level (*p*-value); Mean RR = Mean of RR intervals; SDNN = Standard deviation of the NN intervals; Mean HR, = Mean of heart rate; RMSSD = Root means square of successive NN intervals differences; NN50 = Number of interval differences of successive NN intervals greater than 50 ms; pNN50 = Proportion derived by dividing NN50 by the total number of NN intervals; VLF = Very low frequency; LF = low frequency; HF = High frequency; LF/HF = Low Frequency to High-Frequency ratio.

A mixed ANOVA with a 95% confidence interval was conducted to evaluate the within-subjects effects before and after each shift. Specifically, Mean RR, SDNN, Mean HR, RMSSD, NN50, pNN50, VLF, and HF showed a significant difference (Sig. < 0.050) with detailed results in Table 4.

Table 4. Summary of Mixed ANOVA Tests Within-Subjects Effects.

Measure	df	Mean Square (95% CI)	F	Sig.
Mean RR	1	0.041	59.437	0.000 **
SDNN	1	0.095	7.461	0.008 **
Mean HR	1	0.041	59.432	0.000 **
RMSSD	1	0.254	15.734	0.000 **
NN50	1	1.989	10.063	0.002 **
pNN50	1	1.723	10.807	0.002 **
VLF	1	0.678	4.379	0.041 *
LF	1	0.140	1.847	0.179
HF	1	0.571	7.695	0.007 **
LF/HF	1	0.146	2.710	0.105

* $p < 0.050$, ** $p < 0.010$. Abbreviations: df = degrees of freedom; Mean Square (95% CI) = Variance estimate (sum of squares/df) with 95% confidence interval for the mean difference; F = F-statistic (ratio of between-group variance to within-group variance); Sig. = significance level (*p*-value); Mean RR = Mean of RR intervals; SDNN = Standard deviation of the NN intervals; Mean HR, = Mean of heart rate; RMSSD = Root means square of successive NN intervals differences; NN50 = Number of interval differences of successive NN intervals greater than 50 ms; pNN50 = Proportion derived by dividing NN50 by the total number of NN intervals; VLF = Very low frequency; LF = low frequency; HF = High frequency; LF/HF = Low Frequency to High-Frequency ratio.

Moreover, the Tests of Within-Subjects Contrasts from Mixed ANOVA revealed significant interactions of before-after-shift and shift type (morning, afternoon, and night) for both Mean RR (F = 10.726, $p < 0.001$) and Mean HR (F = 10.726, $p < 0.001$). These indicate changes in HRV metrics from before to after work shifts differ significantly across each type. In Figure 3a, the profile plot showed that the after-shift Mean RR increased sharply during afternoon and night shifts compared to the morning shift. In contrast with Mean RR, Figure 3b shows that after-shift heart rate decreases were larger during afternoon and night shifts compared to the morning shift.

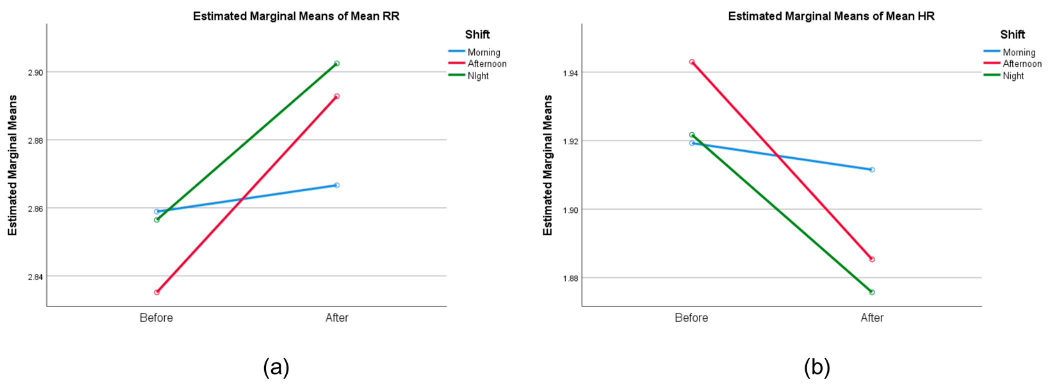

Figure 3. (**a**) Profile Plots Estimated Marginal Means of Mean RR, (**b**) Profile Plots Estimated Marginal Means of Mean HR. Abbreviations: Mean RR = Mean of RR intervals; Mean HR = Mean of heart rate.

To further investigate the relationship between HRV and SOFI measurements, Pearson's Correlation Test was conducted. The analysis showed significant correlations between HRV and SOFI variables, as reflected in Pearson's R-scores in Table 5. These findings highlight the correlation between objective (HRV) and subjective (SOFI) measures of fatigue, providing deeper insight into how work shifts affect nurses' physical and mental states.

Table 5. Summary of HRV and SOFI Pearson's Correlation.

Pair	Pearson's R (95% CI)
SDNN and Sleepiness	−0.222
SDNN and Physical Exertion	−0.214
SDNN and Physical Discomfort	−0.244
Mean HR and Sleepiness	0.230
RMSSD and Sleepiness	−0.275 *
NN50 and Sleepiness	−0.306 *
pNN50 and Sleepiness	−0.306 *
VLF and Lack of Motivation	−0.230
VLF and Sleepiness	−0.231
VLF and Physical Exertion	−0.260 *
VLF and Physical Discomfort	−0.268 *
LF and Physical Exertion	−0.220
LF and Physical Discomfort	−0.225
HF and Sleepiness	−0.230
HF and Physical Discomfort	−0.227

* $p < 0.050$. Abbreviations: Pearson's R = Pearson's correlation coefficient (measure of linear correlation between two variables); 95% CI = 95% confidence interval; Mean RR = Mean of RR intervals; SDNN = Standard deviation of the NN intervals; Mean HR, = Mean of heart rate; RMSSD = Root means square of successive NN intervals differences; NN50 = Number of interval differences of successive NN intervals greater than 50 ms; pNN50 = Proportion derived by dividing NN50 by the total number of NN intervals; VLF = Very low frequency; LF = low frequency; HF = High frequency; LF/HF = Low Frequency to High-Frequency ratio, Lack of Energy = measure of perceived low energy levels; Lack of Motivation = measure of perceived deficiency in drive or willingness to perform tasks; Sleepiness = measure of the tendency to feel drowsy or have difficulty staying awake; Physical Exertion = measure of the perceived physical strain or effort; Physical Discomfort = measure of perceived physical pain or discomfort; Total Score = aggregate fatigue score (sum of individual subscale scores).

3.2. Fatigue Classification

The classifiers used in the model were Logistic Regression, SVM, and k-Nearest Neighbor. The analysis showed that the SVM classifier with Fine Gaussian RBF (radial basis function) kernel generated the highest accuracy and F1 score, as shown in Table 6. These are similar to the findings of a previous study, in which SVM was one of the best-performing algorithms [27]. The accuracy of training and testing data reached 97.58% and 81.00%, respectively. Precision and recall are higher than the other classifiers, resulting in a better F1 score (81%) with a relatively average running time (1.6 s).

Table 6. Classification Model Performance Evaluation.

Classifier	Accuracy (Training)	Accuracy (Testing)	Precision	Recall	F1-Score	Computation Time
Logistic Regression	0.6348	0.4722	0.6200	0.4700	0.4800	1.13
SVM (Linear)	0.6011	0.6110	0.7500	0.6100	0.6400	0.83
SVM (Quadratic)	0.8790	0.5556	0.6100	0.5600	0.5800	1.37
SVM (Cubic)	0.9839	0.5556	0.6100	0.5600	0.5800	1.45
SVM (Fine Gaussian)	0.9758	0.8148	0.8100	0.8100	0.8100	1.60
SVM (Coarse Gaussian)	0.7581	0.6944	0.7300	0.6900	0.7100	1.57
k-NN	0.9609	0.5278	0.5300	0.5200	0.5200	3.04

Abbreviations: Classifier = The machine-learning algorithm used (e.g., Logistic Regression, SVM variants, and k-NN); Accuracy (Training) = The percentage of correctly classified instances during the training phase; Accuracy (Testing) = The percentage of correctly classified instances during the testing phase; Precision = The ratio of true positive predictions to the total number of positive predictions; Recall = The ratio of true positive predictions to the actual number of positives; F1-Score = The harmonic mean of precision and recall; Computation Time = The time required to train and/or test the classifier (in seconds).

In addition, we conducted a feature importance analysis to determine the most relevant features. The feature importance of a Fine Gaussian SVM was assessed using a permutation importance approach. In previous healthcare studies, permutation-based methods effectively identified important biomarkers [49]. This method evaluates the importance of each feature by measuring the decrease in model performance when the feature values are randomly shuffled while keeping the model unchanged. As illustrated in Figure 4, features such as LF and SDNN exhibited the highest importance scores, indicating their substantial impact on the ability of the model to predict fatigue levels among nurses. Conversely, features such as the VLF showed relatively lower importance, suggesting a less critical role in the classification task.

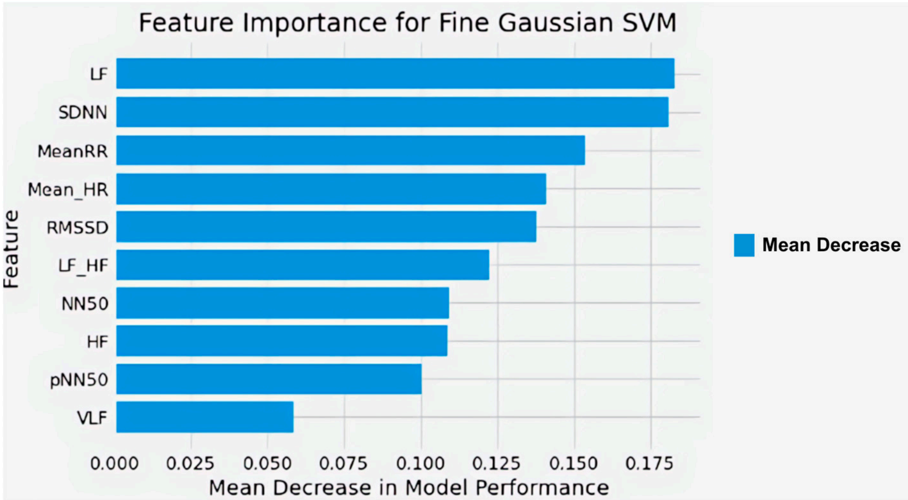

Figure 4. Feature Importance of Fatigue Model. Abbreviations: Mean RR = Mean of RR intervals; SDNN = Standard deviation of the NN intervals; Mean HR, = Mean of heart rate; RMSSD = Root means square of successive NN intervals differences; NN50 = Number of interval differences of successive NN intervals greater than 50 ms; pNN50 = Proportion derived by dividing NN50 by the total number of NN intervals; VLF = Very low frequency; LF = low frequency; HF = High frequency; LF/HF = Low Frequency to High-Frequency ratio.

4. Discussion

4.1. HRV and SOFI Results on Nurses' Shifts

The findings reveal that nurses' autonomic responses to shift work are shaped by both time-of-day effects and cumulative fatigue. While no significant between-subjects differences in HRV metrics were observed across morning, afternoon, and night shifts, within-subjects analyses demonstrated pronounced parasympathetic rebound and sympathetic withdrawal after afternoon and night shifts compared to morning shifts. After work shift slowed heart rate (elevated Mean RR, reduced Mean HR) observed in afternoon and night shifts align with prior studies linking extended or non-daytime shifts to parasympathetic dominance as a fatigue countermeasure [50,51]. This contrasts with the stable HRV profiles during morning shifts, which may benefit from circadian synchronicity and lower cumulative stress. For instance, the significant interaction effects for Mean RR and Mean HR underscore how shift timing modulates autonomic adaptation, with afternoon and night shifts inducing greater HRV fluctuations than morning shifts aligned with natural alertness phases [52,53]. These results evidence that night shifts disrupt the autonomic balance, necessitating stronger recovery responses to offset high cognitive and physical demands [53].

The connection between mental fatigue, emotions, and HRV is rooted in the complex interplay between the autonomic nervous system (ANS) and psychological states. The ANS, comprising the sympathetic and parasympathetic branches, regulates various bodily functions, including heart rate. HRV reflects the balance between these two branches and provides insight into the body's ability to respond to stress and recover. When individuals experience mental fatigue, the sympathetic nervous system becomes overactive, leading to increased heart rate and reduced HRV. Chronic mental fatigue can result in prolonged sympathetic activation, disrupting the normal balance of the ANS and leading to decreased HRV [54]. Emotions also play a crucial role in modulating HRV. Positive emotions, such as joy and contentment, are associated with increased parasympathetic activity and higher HRV, reflecting a state of relaxation and well-being. Conversely, negative emotions, such as anger, anxiety, and sadness, activate the sympathetic nervous system, which leads to lower HRV. This relationship between emotions and HRV underscores the importance of emotional regulation in maintaining optimal autonomic function and overall health [55]. The demanding nature of the nursing workload, coupled with long hours and high-stress environments, can lead to both mental fatigue and emotional distress. Nurses may experience feelings of burnout, frustration, and helplessness, all of which can contribute to decreased HRV and impaired autonomic function. By understanding the link between mental fatigue, emotions, and HRV, healthcare organizations can develop targeted interventions to support nurses' well-being and improve patient care outcomes.

In addition, several dimensions of the SOFI questionnaire showed a significant relationship with HRV. A lack of motivation is associated with decreased VLF, indicating a higher physiological response to stress when motivation decreases. This aligns with previous research by Salmani et al. [56], who highlighted the significant impact of motivation on nurses' overall well-being and stress levels. Sleepiness was negatively correlated with SDNN, Mean HR, RMSSD, NN50, pNN50, VLF, and HF, suggesting that higher levels of fatigue and sleepiness are associated with reductions in HRV parameters. These findings are consistent with prior research indicating that sleepiness reflects disruptions in autonomic nervous system function and the body's ability to adapt to stress [54,57–59]. Physical exhaustion also showed negative correlations with SDNN, VLF, LF, and HF, indicating that high physical activity was associated with decreased HRV. This aligns with the findings of Van Amelsvoort [60], who identified a clear relationship between physical activity and decreased HRV, indicating reduced autonomic nervous system flexibility due to sustained physical demands. Physical Discomfort was negatively correlated with SDNN, VLF, LF, and HF scores. In a study by Jarczok et al. [61], it was found that elevated levels of stress and physical discomfort were associated with decreased HRV, indicating a higher risk of cardiovascular issues and reduced stress resilience. These findings underscore the importance of workload management and working conditions that support nurses' physical and mental health to minimize the risk of ongoing stress and burnout.

4.2. Nurses' Fatigue Classification Modeling

Through this research, it was found that the Fine Gaussian SVM exhibited the best performance among the classifiers with the highest accuracy and F1 score. HRV metrics are complex physiological signals that exhibit nonlinear relationships with fatigue levels. Fine Gaussian SVM uses a radial basis function (RBF) kernel, which is effective for nonlinear classification problems by mapping data into a higher-dimensional space for complex decision boundaries. Previous research shows that approximating Gaussian RBF kernels can significantly speed up SVM classification without losing accuracy [62]. The "Fine" aspect in Fine Gaussian SVM refers to a small kernel scale (sigma), leading to a highly sensitive and detailed decision boundary. Owing to this fine-tuned boundary, the Fine Gaussian SVM can achieve higher precision and recall, leading to a better F1 score. It excels in balancing sensitivity and specificity, which are crucial in healthcare-related models, where both false positives and false negatives can have significant consequences.

In this case, while Logistic Regression is a solid baseline model, it is inherently linear and may struggle with nonlinear relationships, which might not capture all the complexities in HRV data. Linear, quadratic, and cubic SVM have different decision boundaries in capturing complex patterns in the data. The Coarse Gaussian SVM also has a broader and simpler decision boundary that might underfit the data and lead to lower performance. Meanwhile, k-NN is a distance-based classifier that can be effective in some scenarios, but it may not handle high-dimensional data as efficiently as SVMs. Thus, the Fine Gaussian SVM level of accuracy surpasses that typically achieved by Logistic Regression and k-NN, which often struggle to achieve similar performance metrics in complex classification tasks involving physiological data [63].

The use of SMOTE helped mitigate the issue of imbalanced data, a common challenge in medical datasets where one class (e.g., fatigue) might be underrepresented. In previous research, SMOTE implementation in Fine Gaussian SVM models led to improved accuracy rates, from 65.2% without SMOTE to 80% with SMOTE [64]. Despite its detailed decision-making, the Fine Gaussian SVM in this study maintained a relatively medium running time (1.6 s, in this case), making it both effective and efficient. This is particularly important in real-time or near-real-time fatigue-detection applications.

In addition, feature importance analysis for the Fine Gaussian SVM model provided further insights into the predictive power of individual HRV metrics. Using a permutation-based feature importance approach, it was found that the LF and SDNN were among the most critical features influencing the performance of the model. These features are highly correlated with physiological responses associated with fatigue levels, emphasizing their relevance in fatigue detection [65]. The mean RR and HR also demonstrated substantial contributions, highlighting the significance of average heart-rate characteristics in capturing fatigue-related physiological changes. In contrast, features such as VLF had lower importance scores, suggesting limited utility in enhancing the model's predictive capabilities. Previous research has shown that permutation-based feature importance effectively identifies important biomarkers and improves prediction accuracy in machine-learning models for complex human diseases [56]. These findings align with the nature of HRV metrics, where certain frequency-domain and time-domain measures are more sensitive to autonomic nervous system activity and fatigue indicators. This comprehensive feature analysis not only confirms the robustness of the model but also provides a foundation for future work in selecting the most impactful physiological indicators for nurse fatigue monitoring.

Compared to established theoretical frameworks, such as the three-process model, which considers homeostatic sleep drive, circadian rhythms, and sleep inertia [66], this research adds a layer of objective physiological measurement through HRV with a machine-learning classification model. While the three-process model excels at predicting fatigue based on sleep patterns and time factors, it lacks direct measurement of physiological states during wakefulness, which the SVM Fine Gaussian model provides, offering complementary insights rather than contradictory ones. In addition, HRV data collection using wearable solutions and multi-source data fusion presents a strong option for fatigue monitoring in the workplace and other crucial environments [67]. Based on this finding, machine-learning classifiers for fatigue-detection modeling of nurses appear promising. In future research, an additional step would be integrating the best-performing model into a real-time application for continuous fatigue monitoring/alerting to support nurses' well-being and patient safety.

4.3. Limitation

This study had several limitations. First, the research was conducted in only one hospital. Further research can be conducted into other hospitals with different nursing characteristics. In addition, this study only covers four nurse work areas (ER, Inpatient, ICU, and Operating Room) with specific workload characteristics. It would be interesting if additional research could be expanded to study other nursing work areas, because they have different tasks and workloads. Moreover, although purposive sampling enabled us to specifically target nurses with characteristics and experiences relevant to our research on fatigue, it may introduce inherent selection bias, limiting the generalizability of our findings to the broader nursing population. Lastly, several variables, such as differences in workload between nurses and their sleep quality, may be confounding variables but were not considered in this study. Further studies can include confounding variables to enhance the research results.

5. Conclusions

In conclusion, this study indicates that nurses experience varying fatigue levels depending on their shifts, with night and afternoon shifts causing greater physiological stress and fatigue than morning shifts. This was reflected by HRV changes such as elevated Mean RR and reduced Mean HR. Moreover, significant correlations were found between SOFI dimensions, such as lack of motivation, sleepiness, physical exertion, and physical discomfort, with HRV measures, highlighting how physical and psychological stressors affect nurses' fatigue levels.

Using a Fine Gaussian SVM model in ML for fatigue detection proved to be the most effective approach. This is shown by superior accuracy and F1 scores compared to traditional models such as Logistic Regression, k-NN, and other SVM variants. Integrating SMOTE to address class imbalance further enhanced the model's performance. In contrast to simpler linear models, Fine Gaussian SVMs' ability to handle nonlinear complexities in HRV data provides a distinct advantage in detecting fatigue-related patterns. In addition, the most essential HRV features contributing to the performance of the models were LF and SDNN.

Importantly, comparing this model with other fatigue-detection methods underscores its value in predicting fatigue and potential downstream consequences, such as errors, missed shifts, and patient safety incidents. With HRV-based fatigue modeling, hospital management can develop data-driven strategies for shift rotation schedules, better workload allocation, and enhanced mental and physical support for nurses. In future research, integrating real-time HRV monitoring and predictive systems in clinical environments could offer continuous assessment and proactive fatigue management, reducing the risks associated with chronic nurse fatigue and improving healthcare outcomes overall.

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Institutional Review Board Statement: The study was conducted following the Declaration of Helsinki and approved by the local research ethical committee of Universitas Indonesia Hospital (S-093/KETLIT/RSUI/VII/2024). All procedures were conducted following institutional policies.

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Abbreviations

The following abbreviations are used in this manuscript:

HR	Heart rate
HRV	Heart-rate variability
SOFI	Swedish Occupational Fatigue Inventory
ICU	Intensive care unit
ER	Emergency room
OR	Operating room
ANS	Autonomic nervous system
SNS	Sympathetic nervous system
PNS	Parasympathetic nervous system
ML	Machine learning
TP	True positive
FP	False positive
TN	True negative
FN	False negative
Mean RR	Mean of RR intervals
SDNN	Standard deviation of the NN intervals
Mean HR	Mean of heart rate
RMSSD	Root means square of successive NN intervals differences
NN50	Number of interval differences of successive NN intervals greater than 50 ms
pNN50	Proportion derived by dividing NN50 by the total number of NN intervals
VLF	Very low frequency
LF	Low frequency
HF	High frequency
LF/HF	Low Frequency to High-Frequency ratio
BMI	Body mass index
SVM	Support Vector Machine
KNN	K-Nearest Neighbor
SMOTE	Synthetic Minority Oversampling Technique
RBF	Radial basis function

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