УДК 004. 056.55:004.312.2 **doi: 10.26906/SUNZ.2025.1.143-149**

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SYSTEM FOR DETECTING CRITICAL HUMAN HEALTH CONDITIONS BASED ON THE ANALYSIS OF PHYSIOLOGICAL INDICATORS

Abstract. Relevance. The modern increase in cardiovascular diseases, diabetes, and psychological disorders, particularly post-traumatic stress disorder (PTSD), necessitates the implementation of intelligent health monitoring systems. WHO statistics indicate 15 million premature deaths annually, with 32% attributed to cardiovascular diseases. Additionally, the war in Ukraine has significantly impacted stress levels among the population, increasing mortality risks. Traditional monitoring methods do not ensure timely detection of critical conditions, making the adoption of AI-based automated solutions essential. **The object** of this study is a system for detecting critical human health conditions based on the analysis of biometric indicators and their dynamics using machine learning methods. The aim of the article is to develop and evaluate the effectiveness of an automatic system for detecting critical health conditions that operates using wearable devices and artificial intelligence algorithms. To achieve this goal, a stress level classifier based on physiological indicators was implemented, and a comparative analysis of two algorithms, MLPClassifier and RandomForestClassifier, was conducted. **As a result** of the research, an architecture for a continuous health monitoring system was proposed, an algorithm for stress level assessment using ECG, EDA, BCP, and breathing patterns as input parameters were developed, and MLP and Random Forest classifiers were trained, and tested on a dataset of 65 participants. MLPClassifier demonstrated higher classification accuracy (91.3%), confirming its effectiveness for monitoring critical health conditions.

Keywords: health monitoring system, critical conditions, wearable sensors, electrocardiogram, machine learning, classification, MLPClassifier, RandomForestClassifier, telemedicine, biophysiological indicators.

Introduction

Problem Statement. Modern trends indicate that the global population is experiencing an increasing tendency toward premature deaths. According to WHO data, approximately 15 million people aged 30–70 die prematurely each year. Of these, 32% are due to cardiovascular diseases, 17% to cancer, 8% to injuries and accidents, and 7% to respiratory diseases and infections (Fig. 1).

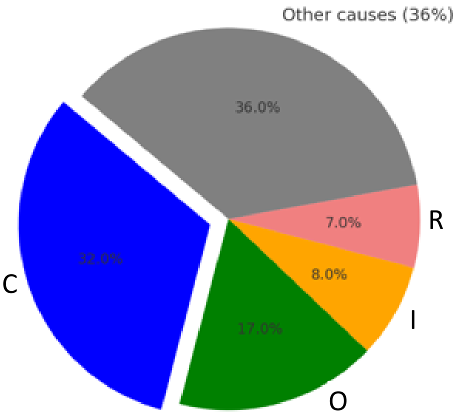


Fig. 1. Diagram of Causes of Human Mortality:
C – Cardiovascular diseases (32%);
R – Respiratory and infectious diseases (7%);
I – Injuries and accidents (8%);
O – Oncological diseases (17%)

Statistics show that 85% of these deaths occur in low- and middle-income countries. This is linked to risk factors such as a sedentary lifestyle, increased stress levels, environmental degradation, and the rising prevalence of diabetes and obesity. In addition to the growing number of psychological disorders (around 3–4 million Ukrainians show signs of PTSD), the war in Ukraine has led to a 15–20% increase in premature mortality [1].

Moreover, over 400,000 public infrastructure facilities (approximately 2.7% of all buildings in Ukraine) have been damaged by shelling, including more than 57,086 residential buildings and 126 medical institutions. This has further deteriorated living conditions and healthcare systems. According to research, the highest levels of loneliness among adults are observed in Eastern European countries. There, 7.5% of young people and 9.6% of middle-aged individuals report feelings of loneliness. Among older adults over 60, this figure rises to 21.3%. In Northern Europe, loneliness levels are lower: 2.9% among young people, 2.7% among middle-aged individuals, and 5.3% among the elderly.

It is crucial to understand that loneliness has serious health consequences. Scientific studies have identified a significant link between loneliness and an increased risk of severe illnesses. Loneliness and social isolation are associated with a higher probability of premature death, cardiovascular diseases, stroke, and type 2 diabetes. In particular, loneliness increases the risk of premature death by approximately 30%.

Remote health monitoring and telemedicine are highly relevant today, requiring the development of new approaches and methods [2], as well as the creation of assistants and support systems for people with disabilities [3]. Looking at such negative statistics, as well as social and economic risks, the relevance of these problems leads humanity to the idea of a comprehensive approach to preventing and detecting critical health conditions. The main tools for reducing premature mortality include:

- medical and personal health monitoring;
- analysis and mitigation of risk factors;
- promotion of a healthy lifestyle;
- reduction of environmental hazards;
- vaccination and infection control.

The further development of a comprehensive approach to preventing critical health conditions (see Table 1) will be driven by technological trends (AI in medical diagnostics and telemedicine) and adherence to key system principles:

- continuous monitoring;
- personalized approaches;
- integration of multidisciplinary data;
- proactive response.

These improvements will enhance the accuracy of disease prediction and, as a result, significantly reduce mortality rates among the population. The following physiological markers of critical health conditions have been selected for this study: ECG, Blood Circulation Pulse (BCP), Breathing Pattern, and Electrodermal Activity (EDA).

Table 1– **Development of Critical Health Condition Prevention**

Diagnosis Level	Treatment Methods	Disease Detection Technologies	Health Condition Indicators	Expected Outcome
Primary Prevention	– Healthy lifestyle – Regular medical check-ups –Proper nutrition	– Mobile monitoring apps – Fitness trackers – Genetic testing	– Biometric indicators – Heredity – Age and gender	– Prevention of disease occurrence
Secondary Prevention	– Early diagnosis – In-depth examination – Monitoring of risk groups	– Artificial intelligence – MRI/CT diagnostics – Biomarker analysis	– Deviations in tests – Risk symptoms – Changes in the body	– Stopping disease progression
Tertiary Prevention	– Rehabilitation – Correction of complications – Psychological support	– Personalized medicine – Telemedicine – Neural networks	– Treatment dynamics – Quality of life – Psycho-emotional state	– Minimization of disease consequences
Predictive Level	– Risk prediction – Individual forecasting – Preventive measures	– Big Data analysis – Genomic medicine – Machine learning	– Genetic profile – Behavioral patterns – Social factors	– Proactive health management

ECG is a critical indicator for assessing heart function and diagnosing and monitoring conditions such as arrhythmia, heart failure, and stress. BCP is a circulation indicator reflecting changes in the pulse wave in blood vessels. The Breathing Pattern is used to assess both the physiological and emotional state of a person. Additionally, analyzing the breathing pattern is utilized in HRV (Heart Rate Variability) to evaluate the balance of the autonomic nervous system [4]. Electrodermal Activity refers to the electrical activity of the skin, which changes due to the function of sweat glands. It is used to evaluate emotional state, stress, and the activity of the nervous system.

Analysis of Recent Research and Publications. The article [5] provides a review of smart wearable systems used for monitoring human biological parameters. The authors discuss hardware, sensor technologies, data analysis algorithms, and methods for integrating these devices into healthcare systems. Special attention is given to artificial intelligence and machine learning, which help improve the processing of acquired signals and enhance the accuracy of medical condition prediction. The results demonstrate that AI helps reduce errors in biosignal analysis, while the use of flexible nanomaterials allows for the creation of highly sensitive, wearable sensors and autonomous power sources, which hold promise for improving the independence of devices. However, the study remains largely theoretical, with practical experiments still limited.

The work [6] examines modern optical sensors for non-contact measurement of vital signs. The principles of operation of fluorescent, spectroscopic, and surface plasmon resonance (SPR) sensors are described. Their advantages over traditional electrochemical and mechanical sensors, particularly in terms of accuracy and speed, are analyzed. The results indicate that optical sensors show high precision in measuring biomarkers in blood and saliva and integrating these sensors into smartphones and wearable devices allows for at-home health monitoring. SPR methods enable non-contact analysis of biological fluids with minimal intrusion. However, real-world experiments on the long-term use of these sensors with patients are not included in the study.

The article [7] focuses on the use of wearable devices for monitoring the health of elderly individuals. The primary devices and sensors that monitor heart rate, blood oxygen levels, blood pressure, and physical activity in real time are described. A separate section is dedicated to the use of IoT and cloud technologies, which enable doctors to receive data remotely. The conclusion highlights that wearable devices significantly reduce the need for hospital monitoring, allowing patients to remain at home, while IoT use enables doctors to respond quickly to critical changes in patient status. However, the greatest challenge remains ensuring data security and the energy autonomy of devices.

In the work [8] an overview of current wearable devices for diagnosing and monitoring patients is presented. Biometric sensors, electrochemical sensors, and artificial intelligence in disease prediction are analyzed. Significant attention is given to the future of wearable devices, including their integration with medical databases and augmented reality (AR) technologies. However, the study lacks practical data on the effectiveness of these devices in real-world conditions.

The work [9] discusses the mathematical model of remote photoplethysmography (rPPG), based on optical and physiological properties of light reflection from the skin. The article analyzes key rPPG methods for extracting pulse signals from video recordings, including Blind Source Separation (PCA, ICA), CHROM, PBV, and 2SR. The main contribution of the paper is a detailed theoretical analysis of rPPG principles, enabling the development of new algorithms for specific tasks. The authors propose a new approach called "Plane-Orthogonal-to-Skin" (POS), which uses the projection of a color vector onto a plane orthogonal to skin tone to improve pulse signal extraction. However, the proposed method is more focused on theoretical analysis than practical clinical application, and some methods may have errors under different lighting conditions. Furthermore, the POS method does not fully account for the variability in light reflection from skin of people with different skin types.

The analysis shows that modern health monitoring systems significantly expand the possibilities for controlling the physical condition of individuals. Future developments in health monitoring should focus on the integration of wearable and stationary systems, improving device autonomy, enhancing measurement accuracy, and expanding telemedicine capabilities.

After analyzing the characteristics and features of the wearable devices described for health monitoring, it can be concluded that these devices have a high cost, do not provide a comprehensive approach to health monitoring, have a limited monitoring duration, require a continuous Internet connection, and are not sufficiently accurate. However, the accumulation of primary biometric data through wearable sensors is insufficient to obtain valuable clinical information. A comprehensive development of methods for processing and interpreting the obtained data is needed, allowing for a transition from quantitative indicators to a qualitative assessment of the human functional state. This approach reflects the effectiveness of performing certain activities and the level of regulatory system tension in the body. Classifying functional states allows for a transition from a continuous stream of various biometric data to discrete categories with clear physiological and clinical interpretations. Several main functional states are identified: physiological norm (optimal state), functional tension, overstrain (distress), exhaustion, and pathological state. Each of these states is characterized by specific changes in the functioning of physiological systems and can be identified by a set of objective indicators.

The main problem in classifying functional states is the selection of informative features. Collected biometric data contains a significant amount of redundant information and noise, which complicates their direct use for classification and is further complicated by the high individual variability of physiological indicators.

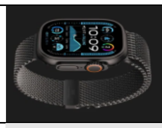
Artificial intelligence offers the necessary tools for solving the problem of classifying functional states. Unlike traditional statistical methods, machine learning algorithms are capable of working with large amounts of unstructured data, identifying hidden patterns, and adapting to individual user characteristics. Among the classical machine learning methods, the most effective for classifying functional states are the Support Vector Machine (SVM), Random Forest, and Multi-Layer Perceptron (MLP) [10, 11].

The goal of the work is to develop a model of a system for detecting critical health conditions and stress levels in humans based on the analysis of physiological indicators, which will provide continuous remote monitoring of the patient's condition using portable devices.

To achieve the stated goal, the following tasks must be solved:

- development of a model for detecting critical human states;
- development of an algorithm for the stress level sensor based on the medical data obtained from the patient;
- implementation of classifiers based on machine learning methods (MLP and Random Forest) for classifying stress levels based on the patient's biophysical data;
- comparative analysis of classification accuracy based on MLP and Random Forest.

Table 2 – **Wearable Devices for Home Use**

System Name	Description of Main Functions of the System	System Drawbacks	Demonstration
Apple Watch	Measurement of pulse rate, ECG, blood oxygen saturation (Spo2)	Inaccuracy of measurements compared to medical devices, low battery life, dependency on the Apple ecosystem.	
BioIntelliSense BioSticker	Continuous monitoring of heart rate, body temperature, body movement tracking, remote monitoring capability.	Limited duration of operation for a single sticker (up to 30 days), measurement inaccuracies during movement, system dependence on a stable internet connection.	
CarePredict Tempo	Tracking the daily activity of elderly people, communication function with caregivers.	High cost of the system, limited device autonomy, dependency on wearing the device.	
Withings BPM Core	Measurement of blood pressure, ECG, heart sound recording	Difficulty of use, dependence on mobile app and internet connection, external noise or body movements may affect measurement results.	
Elderly Care Systems (Vayyar Home, KamiCare, Walabot)	Fall detection without wearable sensors, tracking movement and human activity, tracking breathing at high frequencies through walls	Dependence of accuracy on proper placement of sensors, recognition issues in low light conditions, high installation and maintenance costs.	

Main Content

This work proposes a model of a system for detecting critical health conditions and stress levels in humans based on the analysis of physiological indicators, designed to trigger medical services in case one or more health indicators exceed critical thresholds (fig. 2).

The model includes the following modules – data collection module (physiological indicators), data analysis module, and data storage module. The purpose of each module is as follows:

- the data collection module ensures the collection of data using a wearable device that contains sensors for measuring specific physiological parameters of the patient;

- the data analysis module receives and processes the biometric data of the patient using artificial intelligence. The system also includes response mechanisms for critical situations, which are implemented through the "decision-making" module. This module contains a closed-loop learning cycle for improving the system based on the processed data received from the data storage module.

- the data storage module ensures the reception and storage of information received from the data analysis module, including biometric data, medical history, age, and full name of the patient. This information is later forwarded for use in the closed-loop learning and system improvement process.

Within the proposed model, an algorithm for detecting stress levels has also been implemented. This algorithm involves the analysis of collected data from an electro-optical heart activity sensor (ECG), an electrical skin activity sensor (EDA), a blood circulation measurement sensor (BCP) based on optical photoplethysmography (PPG) technology, and a combination of accelerometers and optical PPG sensors for tracking breathing patterns (Breathing pattern) using machine learning methods (Fig. 3). A key requirement for the algorithm's functioning is the preliminary accumulation of data to determine the normal state of the body, followed by sensor calibration before directly assessing stress levels based on deviations from the normal state of the indicators. The proposed algorithm is based on a comprehensive approach to analyzing the patient's biophysiological data and consists of several sequential stages of information processing. The first stage is the collection of physiological data, namely: ECG, BCP, EDA, and Breathing pattern. These indicators are the most informative for assessing the psycho-physiological state of a person and the level of stress, as they reflect the autonomic nervous system's response to stress factors.

The next stage involves the preliminary processing of the collected signals, including noise filtering and artifact removal. To improve the accuracy of the analysis, digital filters and adaptive filtering algorithms are used, effectively separating the useful signal from noise components. Special attention is given to removing motion artifacts that could distort the analysis results.

Based on the comprehensive analysis of the obtained parameters, the stress level is determined. For stress level classification, a machine learning algorithm is used, trained on a dataset consisting of data from 65 participants. The system classifies the current stress level as either low or high. To improve classification accuracy, individual user characteristics are taken into account, such as the baseline level of indicators at rest and the dynamics of their changes under stress.

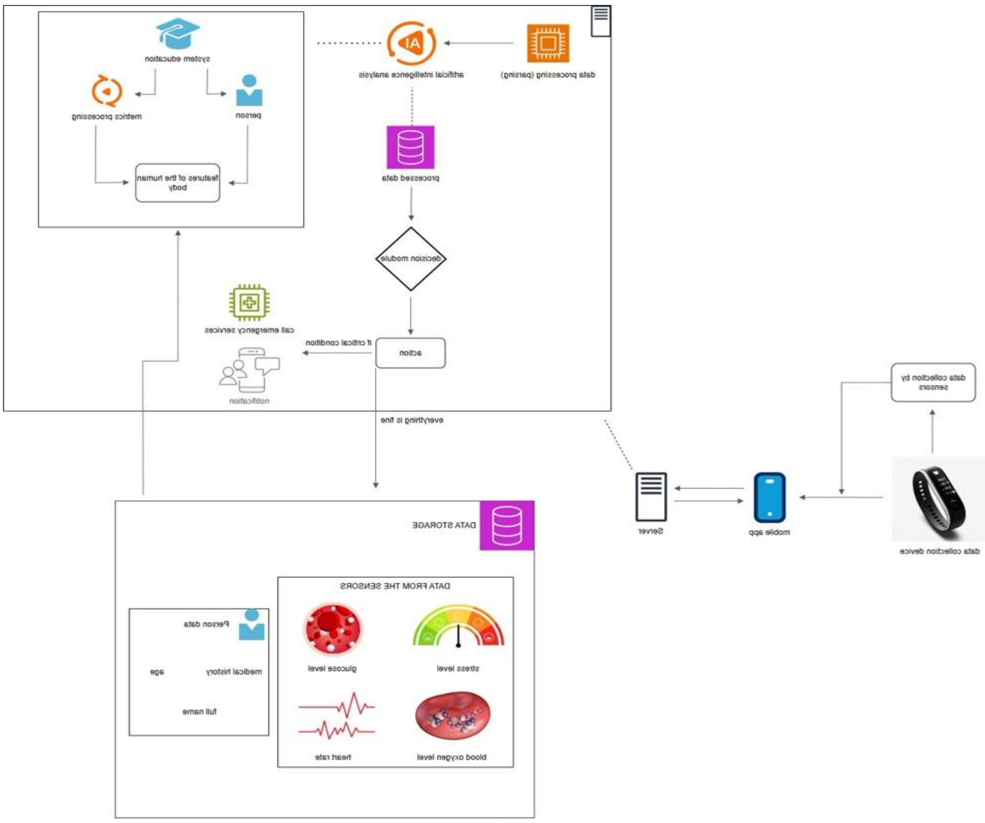


Fig. 2. Diagram of the system model for detecting critical health conditions based on the analysis of physiological indicators

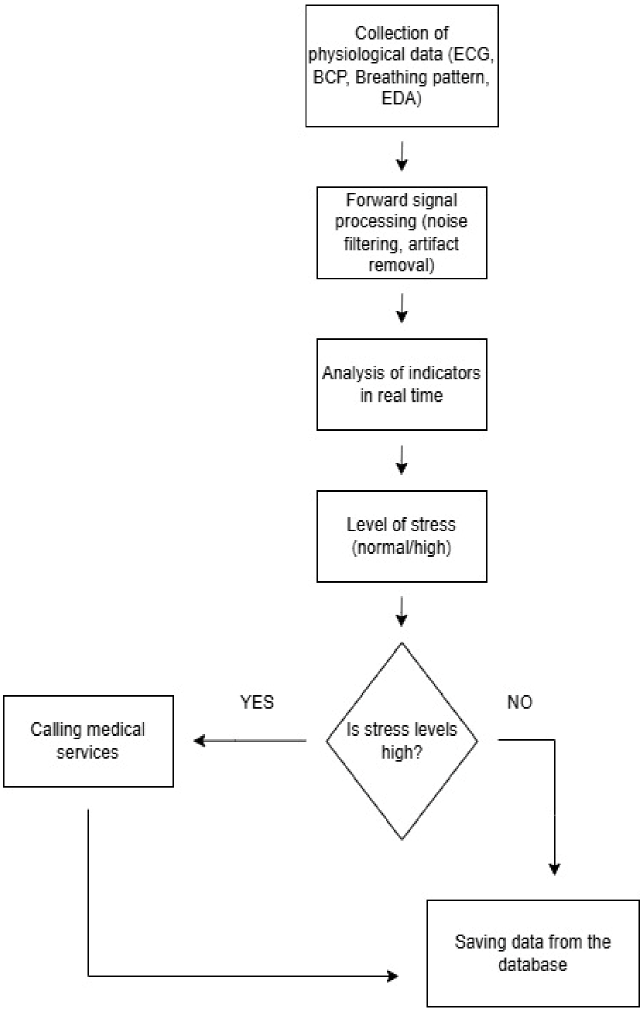


Fig. 3. Algorithm of the Stress Level Sensor Operation

In the case of detecting a high-stress level, the system activates the medical service call mechanism. Simultaneously, the data is saved in a database for further analysis and the formation of recommendations. If the stress level is determined to be normal, the data is also stored in the database to track the dynamics of the indicators over time.

In this study, a dataset based on data from 65 participants is used to train classifiers. This dataset includes facial video, audio, and physiological signals, from which the physiological indicators are considered for analysis. A graph based on these data is shown in Figure 4. The physiological indicators used in the study include:

- ECG (electrical activity of the heart): The ECG line is demonstrated with an amplitude range of -0.5 to 1.5, displaying the typical pattern with R-peaks corresponding to ventricular contractions. During stress (indicated in red), changes in the heart rate and the amplitude of the R-peaks can be observed as part of the physiological response to stress;
- Electrodermal Activity (EDA): A physiological indicator for measuring changes in the electrical properties of the skin, demonstrated on a scale from 2.0 to 2.4 microsiemens (µS) along the Y-axis. During stress, there is a decrease in the EDA values (from 2.3 µS to 2.1 µS), indicating a change in skin conductivity;
- Breathing Pattern: A measure of the rhythm, depth, frequency, and overall structure of breathing movements, shown by a curve with an amplitude range from -1.5 to -0.5. During stress, a deeper and more controlled breathing pattern is often observed, which is a common response to stress;
- Blood Circulation Pulse (BCP): This indicator reflects periodic changes in blood volume and pressure in the blood vessels associated with heartbeats. The curve is shown with clear pulsatile waves ranging from 60-120 beats per minute. During stress (red zones), an increase in the amplitude of the pulse waves is observed.

The lower part of the graph (Predicted stress level) shows the reference values for stress level distribution into two classes: red – high-stress level, green – normal stress level. The scale ranges from 0 to 1, where all values up to 0.5 represent normal levels, and those above 0.5 indicate high-stress levels.

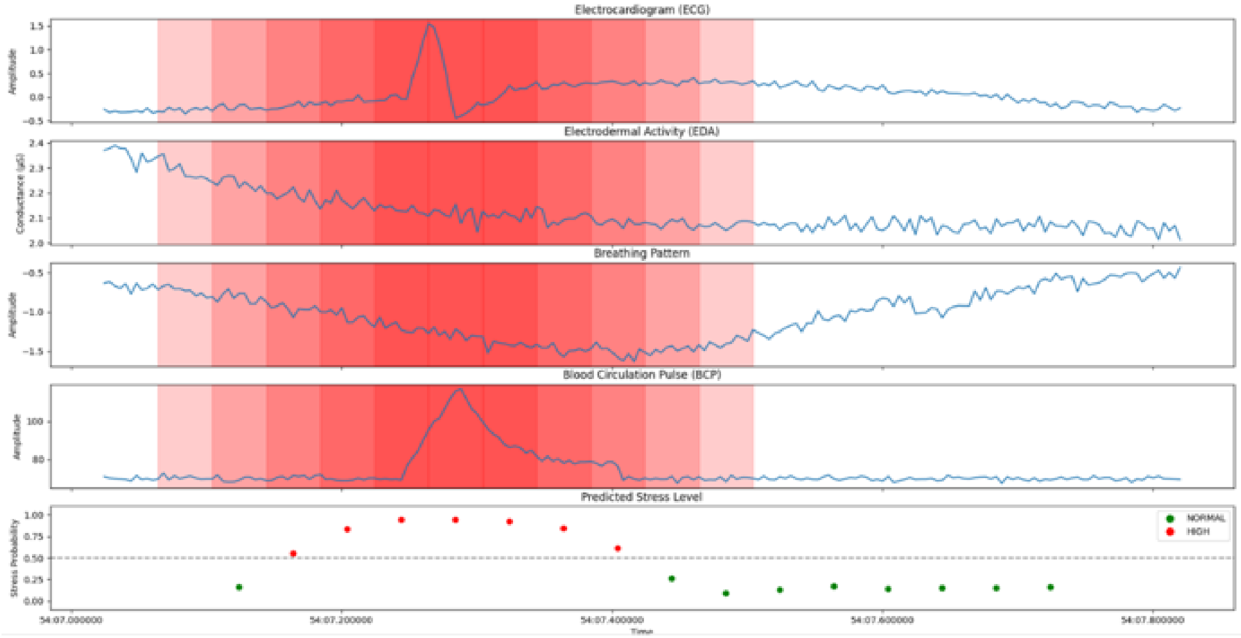


Fig. 4. Dataset for tracking human physiological parameters

The dataset described above serves as input for training the selected machine learning methods, specifically RandomForestClassifier and MLP, whose effectiveness is the subject of research in this work.

Table 3 presents a comparison of the confusion matrix structure for the two machine learning algorithms: Multi-layer Perceptron (MLPClassifier) and Random Forest (RandomForestClassifier).

The results of the study show that MLPClassifier outperforms in all the metrics considered. Specifically, the number of true negatives (TN) for MLPClassifier is 285 compared to 270 for RandomForestClassifier, indicating more accurate identification of negative cases in favor of MLP (+15). MLP also shows fewer false positives (FP) and false negatives (FN) (by 15 and 20, respectively), confirming its higher accuracy and lower error rate in classification. Furthermore, the number of true positives (TP) for MLPClassifier is 20 higher, further emphasizing its effectiveness in identifying positive cases.

Additional performance metrics analysis, shown in Table 4, indicates that the MLPClassifier has a higher accuracy (91.3%) compared to the RandomForest Classifier (82.5%), with an increase of 8.8%. Its precision also significantly outperforms that of the RandomForestClassifier (84.2% vs. 66.7%, a 17.5% improvement). Similarly, the MLPClassifier shows higher recall (80.0% vs. 60.0%, +20.0%), which highlights the model's ability to correctly identify positive cases. The F1-score, combining precision and recall, for the MLPClassifier is 82.1%, while for the RandomForestClassifier it is 63.2% (+18.9%), further confirming the overall advantage of the MLPClassifier.

Based on the two comparative tables (3 and 4) on error structure and metrics, a visualization of the obtained results was created in the form of confusion matrices (Fig. 5) for the RandomForestClassifier and MLP classifiers, which classify data into 2 classes – NORMAL and HIGH. Each matrix shows the number of correct and incorrect predictions.

Table 3– **Confusion Matrix Structure**

Metric	MLPClassifier	RandomForestClassifier	Improvement in MPLClassifier
Accuracy	91.3%	82.5%	+8.8%
Precision	84.2%	66.7%	+17.5%
Recall	80.0%	60.0%	+20.0%
F1-Score	82.1%	63.2%	+18.9%

Table 4– **Comparison of the performance of selected classifiers based on metrics**

Metric	MLPClassifier	RandomForestClassifier	Difference
True negatives (TN)	285	270	+15 in favor of MLP
False Positives (FP)	15	30	-15 in favor of MLP
False Negatives (FN)	20	40	-20 in favor of MLP
True Positives (TP)	80	60	+20 in favor of MLP

For the MLPClassifier model, there are 285 instances where the model correctly identified the NORMAL class and 80 instances where it correctly identified the HIGH class. However, some errors occurred: the model mistakenly classified NORMAL as HIGH 15 times and HIGH as NORMAL 20 times.

In the case of the RandomForestClassifier, 270 instances of the NORMAL class and 60 instances of the HIGH class were correctly identified. However, this model made more errors: it mistakenly predicted NORMAL as HIGH 30 times and HIGH as NORMAL 40 times.

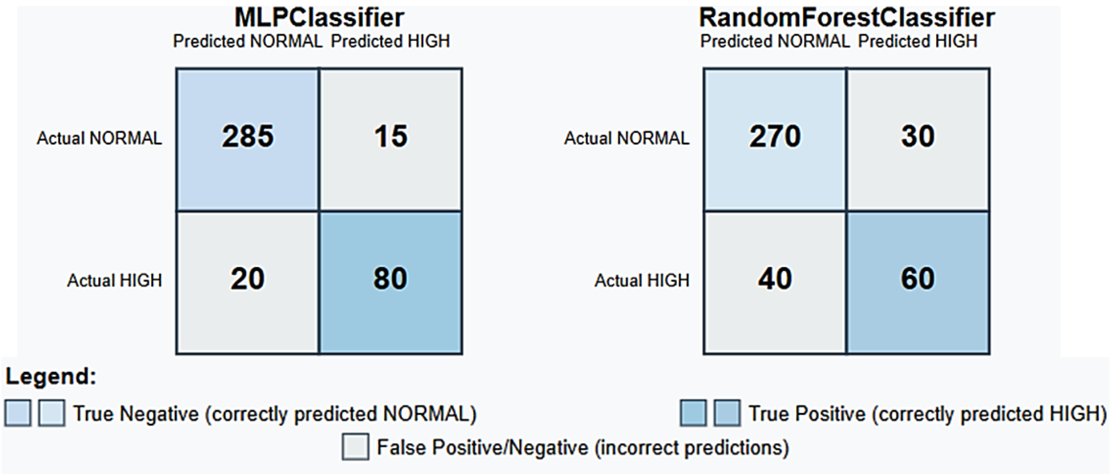


Fig. 5. Confusion matrix of two classifiers: MLP and Random Forest

Compared to the RandomForestClassifier, the MLPClassifier model demonstrates higher accuracy, as it has fewer errors and a greater number of correctly classified objects.

For stress level classification tasks based on biometric data, MLPClassifier demonstrated the best results among the models considered. It provides high accuracy (91.3%) and a good balance between precision and recall for the "HIGH" class (stress), which is crucial for minimizing both false positives and false negatives when determining elevated stress levels.

However, if the goal is to identify which biometric indicators are most significant for determining stress levels, it would be worth considering the use of RandomForestClassifier, which provides a feature importance metric.

Conclusions

The paper presents a system for detecting critical health conditions based on the analysis of physiological indicators. A novel approach is proposed, utilizing wearable sensors for continuous monitoring of vital parameters such as electrocardiogram (ECG), blood circulation pulse (BCP), breathing pattern, and electrodermal activity (EDA).

Using machine learning methods, specifically MLPClassifier and RandomForestClassifier, the system achieves high accuracy in detecting deviations in physiological indicators that may indicate critical conditions. A comparative analysis of the algorithms' performance was conducted, with MLPClassifier demonstrating higher accuracy (91.3%) compared to RandomForestClassifier (82.5%). The results confirm the effectiveness of the proposed approach for remote health monitoring, which is particularly relevant in the context of telemedicine.

The developed system enables the automatic detection of critical health conditions based on physiological parameters, significantly improving the response time to threatening situations. The use of machine learning methods, particularly MLPClassifier, ensures high classification accuracy, making the system promising for implementation in telemedicine services, rehabilitation programs, and personal monitoring systems. Future research will focus on optimizing algorithms, expanding the dataset, and improving the system's adaptation to individual users' physiological characteristics.

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Received (Надійшла) 06.01.2025
Accepted for publication (Прийнята до друку) 05.03.2025

Система виявлення критичних станів здоров'я людини на основі аналізу фізіологічних показників

О. Ю. Барковська, Я. С. Ні, А. О. Гаврашенко, Є. О. Перетяка, А. О. Романенко

Анотація. Актуальність. Сучасний ріст захворювань серцево-судинної системи, діабету та психологічних розладів, зокрема посттравматичного стресового розладу (ПТСР), вимагає впровадження інтелектуальних систем моніторингу стану здоров'я. Статистика ВООЗ вказує на 15 мільйонів передчасних смертей щороку, причому 32% припадає на серцево-судинні захворювання. Крім того, війна в Україні суттєво вплинула на рівень стресу серед населення, що підвищує ризик смертності. Традиційні методи моніторингу не забезпечують оперативного виявлення критичних станів, що робить необхідним застосування автоматизованих рішень на основі штучного інтелекту. **Об'єктом дослідження** є система виявлення критичних станів здоров'я людини, що базується на аналізі біометричних показників та їхньої динаміки за допомогою методів машинного навчання. **Метою статті** є розробка та оцінка ефективності системи автоматичного виявлення критичних станів здоров'я, що працює на основі носимих пристроїв і алгоритмів штучного інтелекту. Для досягнення цієї мети реалізовано класифікатор рівня стресу на основі фізіологічних показників та проведено порівняльний аналіз двох алгоритмів: MLPClassifier та RandomForestClassifier. **В результаті** провеедних досліджень запропоновано архітектуру системи безперервного моніторингу критичних станів здоров'я, розроблено алгоритм оцінки рівня стресу, що використовує ECG, EDA, BCP та Breathing pattern як вхідні параметри, навчено та протестовано класифікатори MLP та Random Forest на датасеті із 65 учасниками. MLPClassifier продемонстрував вищу точність класифікації (91.3%), що підтверджує його ефективність для моніторингу критичних станів здоров'я.

Ключові слова: система моніторингу здоров'я, критичні стани, носимі сенсори, електрокардіограма, машинне навчання, класифікація, MLPClassifier, RandomForestClassifier, телемедицина, біофізіологічні показники.