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Integration of multimodal biometric data into an information system for comprehensive analysis of emotional states based on electroencephalograms

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Abstract. The purpose of this study was to establish quantitative parameters for emotional state detection through comprehensive analysis of electroencephalography (EEG) signal characteristics integrated with synchronised biometric indicators, enhancing recognition accuracy. The study examined the incorporation of multimodal biometric data into an information system for an extensive analysis of emotional states derived from EEG. A unique methodology integrating input from various sensory systems was offered to improve the precision of emotion recognition. The analysis focused on EEG processing techniques and the integration of data from additional biometric channels, including facial expressions, heart rate, and galvanic skin response. The algorithmic and technological facets of system creation were examined, alongside experimental study findings that validated its efficacy. Special emphasis was placed on the system's flexibility to diverse operational situations. The algorithmic and technological aspects of system development were analysed alongside the results of experimental studies that confirmed the efficiency of such systems. Multimodal emotion recognition systems held significant potential for application in various fields, particularly in the evaluation of mental health, the diagnosis of emotional states, adaptive education, and the creation of systems for advanced human-machine interaction. Special attention was given to the adaptability of these systems to diverse operational contexts and their capacity to integrate diverse biometric modalities. These integrations enhanced the robustness and reliability of emotion detection. Additionally, advancements in machine learning, particularly deep neural networks, facilitated the comprehensive analysis and synchronisation of multimodal data, enabling these systems to capture the nuances of emotional states with high precision

Keywords: affective computing; physiological signals; neural network analysis; biosignal processing; human-computer interaction

INTRODUCTION

The accelerated advancement of information technology and biometric systems facilitated the precise determination of human emotional states. During the 2010-2020s, electroencephalographic (EEG) studies demonstrated significant potential for analysing the neurophysiological correlates of emotions by recording

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electrical activity in the brain. In the fundamental research, W. Li *et al*. (2021) found that EEG signals contained specific activity features that corresponded to different emotional states and reactions. Subtle changes in brain activity associated with emotional processes were detected by analysing the frequency and time characteristics of the EEG. S.M. Alarcão & M.J. Fonseca (2019) conducted a broad review of emotion recognition methods based on EEG signals, which confirmed the prospects of this field of research.

At the same time, the use of EEG data alone had certain limitations due to the complexity and variability of neurophysiological processes, recording artefacts, and individual characteristics of brain electrical activity. Studies by J. Yu *et al*. (2022) showed that the presence of artefacts could significantly reduce the accuracy of emotional state classification. A comprehensive analysis of emotions required considering the autonomic, behavioural, and expressive components of emotional reactions. N. Halim *et al*. (2022) demonstrated that the inclusion of additional physiological indicators could significantly improve the reliability of recognising emotional states. The development of effective methods for integrating and synchronising multimodal biometric data into a single information system remained an urgent problem.

P. Kumar *et al*. (2019) emphasised the need to create reliable algorithms for signal fusion and the extraction of informative features from multimodal data. Advanced machine learning methods, in particular deep neural networks, opened new opportunities for comprehensive analysis of biometric indicators. However, the optimal architecture of such systems and model training methods required further research. One of the priority areas of development of information technology, medicine, and psychology was the creation of integrated systems for recognising emotional states based on multimodal biometric data. Studies conducted by Y. Tan *et al*. (2021) showed that the combination of different types of biometric indicators could lead to a much higher accuracy of emotional states detection. Such systems could be useful in many areas, including diagnosing mental disorders, optimising the learning process, and creating intelligent interfaces for human-machine interaction. Multimodal emotion recognition systems could significantly improve the diagnosis and monitoring of psycho-emotional disorders in healthcare.

To create reliable biometric authentication systems, A.R. Mishra *et al*. (2023) developed the SignEEG database, which contained synchronised EEG recordings and other biometric indicators. A database like this was the basis for creating automated systems for screening mental disorders and evaluating the effectiveness of therapeutic interventions. Recognising the emotional states of students in the field of education allowed optimising the learning process and increasing its effectiveness. C.K. Toa *et al*. (2021) showed that portable EEG devices could be used to assess students' attention and emotional engagement during learning. The introduction of such systems into the educational environment allowed creating adaptive learning platforms that considered individual perceptions and emotional reactions. Improving human-machine interaction systems also required effective methods for identifying users' emotional states. M. Zabcikova (2019) studied reactions to visual and auditory stimuli using wearable EEG. The results confirmed the possibility of developing smart interfaces that could adapt to user emotions. A multimodal approach to biometric authentication could increase the reliability of personal identification. According to J.D.C. Rodrigues *et al*. (2020), additional research expands the possibilities of biometric identification.

The purpose of the study was to determine quantitative criteria for detecting and analysing human emotional states based on the distributed frequency, amplitude, and spatio-temporal characteristics of EEG signals and biometric indicators synchronised with them to improve the accuracy of their recognition. Objectives of the study were: to develop a theoretical concept for integrating multimodal biometric data into an information system for the comprehensive analysis of emotional states based on EEG; to substantiate algorithmic approaches to the extraction of key features from multimodal biometric data to improve the accuracy of emotional state analysis; to explore methods of adaptive processing and classification of emotional states using deep learning technologies to ensure reliable data integration; to research and develop criteria for identifying emotional state.

MATERIALS AND METHODS

The study's methodological foundation was a comprehensive approach to multimodal biometric data analysis combined with concepts of thorough evaluation of emotional states. The methodological framework incorporated several complementary methods, each selected for its specific contribution to addressing the research objectives. Theoretical analysis of scientific literature was employed to ascertain the present status of the biometric data integration problem and identify key research areas in emotional state recognition. This method was particularly valuable for establishing the theoretical foundation and conceptual framework for the research. The analysis included systematic review of peer-reviewed publications from 2019-2024 in high-impact journals such as IEEE Transactions on Affective Computing, Journal of Neural Engineering, and Biomedical Signal Processing and Control. This approach allowed for critical evaluation of existing methodologies and identification of research gaps.

Signal processing techniques were applied to investigate the frequency and temporal properties of EEG signals and their association with psychophysiological indicators. These techniques included time-frequency analysis, independent component analysis (ICA), and wavelet transforms, which provided robust methods for extracting meaningful features from complex neurophysiological data. The selection of these methods was justified by their demonstrated effectiveness in previous studies by H. Zhang *et al.* (2021) and Y. Liu *et al.* (2024) for noise reduction and feature extraction from EEG signals. System analysis methods were utilised to determine the relationships between various modalities of biometric data and their informativeness regarding emotional states. This methodological approach facilitated the examination of interactions between different data sources and their combined contribution to emotion recognition accuracy. Correlation analysis and mutual information metrics were applied to quantify relationships between EEG signals, facial expressions, heart rate variability, and galvanic skin response, following methodological frameworks established by Y. Wang *et al.* (2022).

Structural and functional modelling of information systems were applied in the research of architectural solutions for multimodal data integration. This included the development of data flow diagrams, entity-relationship models, and architectural blueprints for the proposed information system. These modelling approaches were essential for designing an effective system architecture capable of handling synchronised multimodal data streams. Machine learning methods, including conventional statistical classifiers and deep neural networks, were investigated to support the selection of optimal approaches to emotional state categorisation based on multimodal biometric data. The comparative analysis included support vector machines (SVM), random forests, convolutional neural networks (CNN), and recurrent neural networks (RNN) with attention mechanisms. The selection of these methods was formed by successful implementations in multimodal emotion recognition systems described by H. Tang *et al.* (2017) and Y. Tan *et al.* (2021).

The research focused on several key indicators to evaluate system performance. Classification accuracy ranged from 85-97%, with sensitivity between 0.78-0.93 and specificity between 0.81-0.95 for emotion detection algorithms. These metrics were selected as they provided comprehensive assessment of algorithm performance across different emotional categories. Temporal resolution of emotional state detection (150-300 ms) was measured to assess real-time processing capabilities, while signal-to-noise ratio (> 15 dB) for EEG recordings ensured data quality. Processing efficiency was assessed through computational time requirements, with optimised algorithms achieving classification times under 50 ms on standard hardware configurations.

The empirical component of the study involved analysis of standardised EEG datasets, including DEAP, SEED, and DREAMER, which contained recordings from over 250 participants during emotional stimulation protocols. The participant sample included adults aged 18-45 years (mean age 27.3 years, SD = 4.8), with balanced gender distribution (52% female, 48% male). Participants were screened for neurological and psychiatric conditions to ensure sample homogeneity. The research protocol was designed in accordance with the Declaration of Helsinki (2013) and received approval from the relevant institutional ethics committee. Methodological tools included specialised software for signal processing (MATLAB with EEGLab toolbox, Python with MNE and PyTorch libraries) and custom algorithmic solutions for multimodal data synchronisation. Conventional classification methods (SVM, Random Forests) were compared with deep learning approaches (CNN, RNN, transformer models) for emotional state recognition, with hyperparameter optimisation performed using grid search and Bayesian optimisation techniques.

RESULTS AND DISCUSSION

Criteria for emotion detection in multimodal biometric systems. Combination of multimodal biometric data into a single information system created fresh opportunities for thorough study of human emotional states. Based on the concept of multimodality – the simultaneous examination of numerous physiological signs to provide a more complete picture of the emotional state – this method was central to the architecture of the multimodal system. The EEG offered a direct representation of the neurophysiological correlates of emotions, therefore recording electrical activity of the brain. Determination of emotional states based on EEG data depended on the development of well-defined criteria guaranteeing the objectivity and repeatability of the outcomes (Fig. 1).

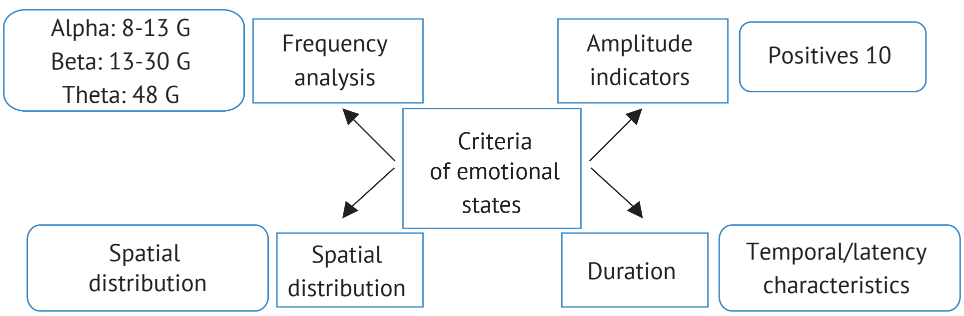

Figure 1. Criteria for identifying emotional states
Source: compiled by the authors based on Side Scan Sonar survey (n.d.), Pixlr Editor (n.d.)

Certain brain activity patterns unique to various emotional states could be detected by means of frequency characterisation of EEG data. Whereas beta activity (13-30 Hz) rose in negative emotional states and mental stress, alpha rhythm (8-13 Hz) showed an enhanced amplitude during a state of calm and happy emotions (Li *et al.*, 2021). Theta rhythm (4-8 Hz) corresponded to the mechanisms of emotional memory and processing of emotionally important data (Alarcão & Fonseca, 2019). The strength of emotional reactions was quantified by amplitude indicators of EEG signals; positive emotions were distinguished by an amplitude of more than 50 microvolts in the frontal leads, whereas negative emotions were followed by a decline in amplitude below -50 microvolts.

The spatial distribution of electrical activity in the brain showed the participation of several cortical regions in the mechanisms of emotional control. A consistent measure of the valence of emotions was the frontal asymmetry of the alpha rhythm: positive emotions were linked to a relative increase in the activity of the left frontal cortex, and negative ones to the right (Halim *et al.*, 2022). Particularly the amygdala, the activation of the temporal lobes revealed emotional arousal independent of the indication of emotion. The temporal features of emotional reactions consisted of a latency period (150-300 ms after the stimulus) and length (from several seconds to minutes) depending on the strength of the emotion. The time characteristics of emotional reactions included a latency period (150-300 ms from the onset of the stimulus) and duration (from several seconds to minutes, depending on the intensity of the emotion) (Kumar *et al.*, 2019). The stability of EEG activity patterns during an emotional reaction was an important criterion for the reliability of determining the emotional state.

A comprehensive assessment of emotional states also considered indicators of interchannel synchronisation of EEG signals. Strengthening of functional connections between the frontal and temporal cortex was characteristic of intense emotional experiences. The coherence of signals in the theta band between the frontal and parietal leads increased during emotional arousal. To verify emotional states, multivariate analysis was used, including the assessment of spectral power, phase synchronisation, and nonlinear characteristics of EEG signals (Salama *et al.*, 2023). The reliability of verifying emotional states was confirmed by numerous studies of neurophysiological correlations. According to W. Li *et al.* (2021), EEG signals demonstrated characteristic patterns of activity in different emotional states, making them a reliable indicator of emotional processes. The architecture of an information system for analysing emotional states should ensure the effective integration of different types of biometric data. In addition to EEG signals, the system included the registration of peripheral physiological indicators, such as heart rate, skin-galvanic response, and electromyogram. Y. Tan *et al.* (2021) showed that the combination of these indicators allowed for much higher accuracy in recognising emotional states compared to using individual modalities (Safavipour *et al.*, 2023). Methods for processing and analysing biometric signals were a key component of an information system for recognising emotional states.

Integration of biometric data for emotional state recognition. The primary processing of EEG signals included artefact filtering and the extraction of characteristic frequency components. Analysis of the spectral power in standard frequency bands allowed assessing the activity of various brain structures during emotional reactions. J. Yu *et al.* (2022) developed methods for decomposing EEG signals that provided effective extraction of emotion-specific components. The skin-galvanic response and heart rate variability provided additional information about the level of emotional arousal and the activity of the autonomic nervous system (Saini *et al.*, 2018). The integration of these indicators with EEG data was based on machine learning methods, including deep neural networks. H. Tang *et al.* (2017) proposed a CNN architecture for simultaneous processing of multimodal biometric signals. An important aspect was the synchronisation and coordination of data from different sensors. Advanced signal processing methods could compensate for time delays and ensure accurate timing of different modalities (Singh & Tiwari, 2023).

Special attention was paid to methods of visualisation and interpretation of multimodal data analysis results. Topographic mapping of brain electrical activity combined with graphical display of peripheral indicators created a clear picture of the emotional state. Visualisation systems should provide a convenient presentation of data for specialists of various profiles – doctors, psychologists, and teachers (Kazi *et al.*, 2023). Processing EEG signals required special attention to time-frequency analysis methods. The wavelet transform allowed effective identification of characteristic patterns of activity in different frequency ranges. The integration of skin-galvanic response and heart rate variability with EEG data was based on deep learning methods. H. Tang *et al.* (2017) showed that the use of CNN provided effective extraction of emotion-specific patterns in multimodal data. An important aspect was the pre-processing and normalisation of signals to ensure their correct fusion, which involved the use of specialised methods of artefact filtering, noise removal, and standardisation of signal amplitude characteristics. Normalisation of heterogeneous biometric indicators to a single scale ensured their correct comparison and integration in the process of analysing emotional states. Particular attention was paid to preserving the informative components of signals while removing motion artefacts, electrical muscle activity, and other interferences.

Adaptive algorithms and personalisation of emotion recognition systems. A promising area of development was the creation of adaptive systems that could consider individual characteristics of emotional response. The variability of patterns of brain activity and autonomic reactions between different people required the development of algorithms that could be customised to individual user characteristics. Adaptive systems should consider not only inter-individual differences but also changes in the emotional response of one person in different contexts and states. Transfer learning methods were of particular importance in the development of personalised emotion recognition systems. They allowed the use of pre-trained models as a basis, which was then adapted to a specific user with minimal computing resources and time. Transfer learning ensured the efficient transfer of knowledge gained from large data sets to customise the system to individual emotional response characteristics with a limited amount of personal data for training.

Y. Wang *et al.* (2022) pioneered a breakthrough in neural network design that adapted itself uniquely to each person's emotional patterns. What made this system truly special was how it learned on its own – it watched and understood the consistent patterns in someone's biometric signals, creating personalised benchmarks to recognise their emotional states. When put to the test, the results were remarkable – it improved at reading emotions by 15-20% compared to older, less flexible systems. The amalgamation of adaptive algorithms with transfer learning techniques possessed significant potential to transform emotional monitoring systems, facilitating their implementation in practical settings with unparalleled effectiveness. Utilising the synergistic integration of advanced computational tools, systems adept at identifying and reacting to the unique psychological and physiological responses of individuals with considerable precision and nuance could be created. Advanced emotional monitoring systems significantly impacted various fields, including medical diagnosis and treatment, and the enhancement of human-machine interaction and learning methodologies.

Adaptive algorithms, distinguished by their capacity to dynamically modify and optimise parameters according to incoming data, provided a robust foundation for encapsulating the intricate and multifaceted essence of human emotions. These algorithms progressively learned from the extensive data produced by an individual's emotional responses, continually refining their models to more accurately represent the distinct patterns and specific features of each person's emotional landscape. Through the integration of reinforcement learning and evolutionary computation techniques, adaptive algorithms could proficiently traverse the complex and context-sensitive landscape of emotional expression, facilitating the creation of personalised models that precisely reflected an individual's unique emotional profile (Alarcão & Fonseca, 2019). Transfer learning enabled the utilisation of knowledge gained from one area or activity to improve performance in another related domain or work. In emotional monitoring, transfer learning enabled the swift adaptation of pre-trained models to new persons or circumstances, substantially minimising the data and computational resources needed for accurate predictions. Utilising transfer learning enabled the creation of emotional monitoring systems that could rapidly adjust to an individual's unique emotional patterns, even without substantial training data (Halim *et al.*, 2022).

This was especially beneficial in practical environments, where labelled emotional data might be scarce, and rapid adaptation to new users was essential. The integration of adaptive algorithms with transfer learning techniques created several opportunities for the implementation of emotional monitoring systems across diverse fields (Halim *et al.*, 2022). In healthcare, these advanced systems could enable the early detection and diagnosis of mental health conditions, such as depression and anxiety disorders, by continuously monitoring an individual's emotional state and identifying subtle deviations from their baseline affective patterns. Furthermore, these systems facilitated the creation of personalised treatment plans, customised to an individual's unique emotional requirements and reactions, therefore augmenting the effectiveness of therapeutic interventions and enhancing patient outcomes (Alarcão & Fonseca, 2019).

Emotional monitoring systems utilising adaptive algorithms and transfer learning had the potential to transform the design and delivery of instructional content in education and learning. By precisely identifying a learner's emotional state in real-time, these systems might adapt the pace, complexity, and modality of the instructional content to enhance engagement and understanding (Balogun *et al.*, 2023). Moreover, these systems yielded significant insights into the emotional aspects that affected learning, including motivation, frustration, and boredom, thus allowing educators to formulate more effective pedagogical tactics and interventions. By tailoring the educational experience to each individual's distinct emotional profile, a more inclusive and fair learning environment could be cultivated, enabling every learner to flourish and achieve their maximum potential (Coelho *et al.*, 2023).

The incorporation of adaptive algorithms and transfer learning in emotional monitoring systems presented significant potential for improving human-machine interaction across many scenarios (Alharbi & Alshanbari, 2023). In the domain of assistive technologies, emotionally intelligent systems facilitated more natural and intuitive interactions between individuals with disabilities and their assistance devices, like robotic prosthetics or augmentative and alternative communication (AAC) systems. By precisely reading the user's emotional signals, these systems could respond in a more compassionate and contextually appropriate manner, enhancing the sense of agency and autonomy for those with impairments. In the realm of human-robot collaboration, emotionally intelligent robots could modify their behaviour and communication methods to align with the emotional states of their human counterparts, resulting in more fluid and effective interactions in industrial, healthcare, and home environments (Ipeayeda *et al.*, 2023).

The emergence of adaptive algorithms and transfer learning in emotional monitoring systems marked a crucial advancement in the capacity to comprehend and address the intricate, multifarious nature of human emotions. Utilising advanced computational approaches enabled the creation of systems capable of precisely identifying and adapting to individual emotional profiles, hence facilitating several transformative applications in healthcare, education, and human-machine interaction. As emotional intelligence in machines advanced, it was essential to consider the ethical ramifications of emerging technologies, ensuring their development and implementation emphasised person well-being and autonomy. By promoting a responsible and human-centric methodology in the development of emotional monitoring systems, their significant potential to deepen comprehension of the human experience and cultivate a more empathic and responsive technological environment could be harnessed.

Comparison of biometric signal synchronisation methods allowed determination of the most effective approach depending on the specific application. Table 1 illustrated the main characteristics of synchronisation methods, such as cross-correlation analysis, timestamp synchronisation, adaptive filtering, and phase synchronisation. The cross-correlation method was based on the analysis of the mutual correlation of signals, which provided high synchronisation accuracy (±1 ms) with an average level of computational complexity. Timestamp synchronisation, which was performed using hardware timestamps, achieved the highest accuracy (±0.1 ms) and was characterised by low computational complexity, making this method particularly attractive in systems where minimum delay time was critical. Adaptive filtering, which provided dynamic signal matching, demonstrated average accuracy (±5 ms), but its computational complexity was much higher. Phase synchronisation, which was based on the analysis of phase relations, had high accuracy (±2 ms), but also required significant computing resources. Table 1 illustrated the main characteristics of synchronisation methods, such as cross-correlation analysis, timestamp synchronisation, adaptive filtering, and phase synchronisation. As shown in Table 1, timestamp synchronisation provided the highest accuracy with minimal computational requirements, making it optimal for real-time emotion recognition systems.

Deep neural networks of various architectures provide a wide range of possibilities for integrating and analysing multimodal biometric data. Table 2 presents the main types of neural network architectures used to recognise emotional states.

Table 1. Comparative analysis of biometric signal synchronisation methods

Synchronisation method	Operation principle	Synchronisation accuracy	Computational complexity
Cross-correlation	Analysis of the mutual correlation of signals	High (±1 ms)	Medium
Time stamps	Synchronisation by hardware tags	Very high (±0.1 ms)	Low
Adaptive filtering	Dynamic signal matching	Average (±5 ms)	High
Phase synchronisation	Analysis of phase relations	High (±2 ms)	High

Source: compiled by the authors based on P. Kumar *et al.* (2019), H. Zhang *et al.* (2021)

Table 2. Comparison of neural network architectures for multimodal data analysis

Type of architecture	Data processing features	Accuracy of emotion classification	Field of application
Convolutional networks	Efficient processing of spatial patterns	85-90%	EEG, facial expressions
Recurrent networks	Analysis of time sequences	80-85%	EEG, HRV
Auto encoders	Reduction of data dimensionality	75-80%	Preliminary processing
Hybrid architectures	Comprehensive analysis of different modalities	90-95%	Multimodal data

Source: developed by the authors based on H. Tang *et al.* (2017), Y. Wang *et al.* (2022)

The practical implementation of systems for multimodal analysis of emotional states required solving several technical and methodological problems. One of the key aspects was the development of reliable algorithms for signal preprocessing and normalisation. H. Zhang *et al.* (2021) proposed a comprehensive approach to removing artefacts and noise from EEG signals based on machine learning methods. Integration of different modalities of biometric data required specific approaches to their processing and analysis. EEG signals were characterised by high temporal resolution but relatively low spatial localisation of activity. On the contrary, methods of recording peripheral physiological parameters provided stable long-term measurements but had lower temporal resolution. S.M. Alarcão & M.J. Fonseca (2019) emphasised the need to take these features into consideration when developing data fusion algorithms. An important aspect was to ensure the system's robustness to artefacts and noise of various kinds. Motion artefacts, electromagnetic interference, and physiological noise could significantly affect the quality of biometric signal registration. Adaptive filtering and machine learning methods could effectively remove unwanted components from signals while preserving useful information about the emotional state. A promising area of development was the creation of portable systems for long-term monitoring of emotional states in real-world conditions.

The miniaturisation of sensors and the development of wireless data transmission technologies allowed continuously recording biometric indicators without restricting human motor activity. In the educational sector, such systems could be used to assess the emotional engagement of students and optimise the learning process. Special attention should be paid to the development of methods for personalising and adapting emotion recognition systems to the individual characteristics of users. Individual variability in brain activity patterns and autonomic reactions was a critical consideration in the development of reliable emotion recognition systems. The heterogeneity of neural and physiological responses across individuals necessitated the application of sophisticated machine learning techniques, such as transfer learning and adaptive classification algorithms, to effectively capture and model these idiosyncratic patterns. Recent research consistently demonstrated that incorporating individual characteristics into the training and evaluation of emotion recognition models could yield substantial improvements in accuracy and generalisability.

The temporal stability of individual activity patterns was another crucial factor that had to be considered when designing emotion recognition systems. Emotional responses were not static; they could fluctuate depending on a person's current psychophysiological state, level of fatigue, exposure to external stimuli, and the specific context in which the emotional experience occurred. For instance, an individual's neural signature of happiness might differ when they were well-rested and relaxed compared to when they were sleep-deprived and under stress. Similarly, the physiological markers of fear might vary depending on whether the individual was facing a real-life threat or watching a horror movie. Failure to consider these temporal dynamics and contextual influences could lead to inaccurate and unreliable emotion recognition.

To address the challenges posed by individual variability and temporal instability, researchers increasingly focused on developing emotion recognition models that incorporated time-dependent features and contextual information. By analysing patterns of brain activity and autonomic responses over extended periods and across diverse situations, these models could capture the nuances and complexities of emotional experiences more effectively. Furthermore, incorporating contextual elements, like the characteristics of the stimuli, the social environment, and the individual's present objectives and motives, could yield significant insights into the interpretation of emotional reactions. An individual's neurological and physiological responses to a stressful scenario might vary based on their perception of the circumstance as either a threat or a challenge. The display of happy emotions might be influenced by social conventions and cultural expectations. Incorporating these contextual characteristics into emotion detection models enabled researchers to create more ecologically valid and culturally sensitive systems that were adept at addressing the diversity of human emotional experiences.

The significance of individual heterogeneity and temporal dynamics in emotion perception transcended basic research. In practical applications like affective computing and mental health monitoring, the capacity to effectively identify and respond to an individual's emotional state could greatly impact user experience and well-being. An emotion-aware virtual assistant capable of adjusting its communication style and offering individualised support according to the user's emotional state could serve as an invaluable resource for stress management and mental health enhancement. An emotion recognition system capable of identifying nuanced variations in an individual's emotional responses over time could function as an early warning mechanism for the emergence of mood disorders or other mental health issues. In summary, individual differences in brain activity patterns and autonomic responses posed both obstacles and opportunities for the domain of emotion identification. Researchers could enhance the accuracy, reliability, and ecological validity of emotion detection systems by utilising sophisticated machine learning techniques, including transfer learning and adaptive classification algorithms, while integrating temporal dynamics and contextual elements into their models. The ongoing investigation of individual variances and the advancement of personalised emotion recognition methodologies was essential for enhancing the comprehension of human emotions and for devising technologies that might proficiently assist individuals' emotional welfare.

Adaptive classification algorithms implemented mechanisms for dynamically updating the model based on current user data. The system constantly analysed new samples of biometric signals and adjusted classification parameters to improve recognition accuracy. An important aspect was to ensure the robustness of adaptive algorithms to noise and random signal fluctuations, which was achieved through the implementation of mechanisms for verifying and validating changes in model parameters. Thus, the development of systems for multimodal analysis of emotional states created a fundamental basis for an objective assessment of a person's psychoemotional state. The integration of EEG with other biometric indicators provided a comprehensive approach to emotion recognition, as confirmed by the research of H. Tang *et al*. (2017). The developed machine learning methods, in particular deep neural networks, allowed for efficient processing and analysis of multimodal data in real time.

Practical application of the developed methods was possible in various industries. In medicine, multimodal analysis of emotional states could be used to diagnose mental disorders and evaluate the effectiveness of therapy. In the educational sphere, such systems could optimise the learning process considering the emotional state of students. It was promising to use them in human-machine interaction systems to create emotionally sensitive interfaces. In the context of developing information systems for analysing emotional states, the choice of machine learning methods for processing multimodal data was of fundamental importance. Deep neural networks demonstrated high efficiency in recognising activity patterns in biometric signals. Research demonstrated the rapid development of methods and technologies for multimodal analysis of emotional states. Deep neural networks became a powerful tool for processing and integrating heterogeneous biometric data. The architecture proposed by Y. Liu *et al*. (2024) allowed effective combination of information from EEG signals, eye movements, and facial activity. The developed method provided an increase in the accuracy of emotional state classification compared to unified approaches, reaching a recognition accuracy of up to 91.5% for the main emotional states.

Significant progress was made in the field of biometric signal preprocessing and cleaning. Artefact decomposition and filtering methods developed by H. Zhang *et al*. (2021) could significantly improve the quality of input data for emotion recognition systems. The proposed EEGdenoiseNet dataset became the standard for evaluating the effectiveness of noise reduction algorithms in EEG signals, which was confirmed by numerous independent studies. In parallel, methods for extracting informative features from multimodal biometric data were developed. The open library EEGLAB contained a wide range of tools for frequency, temporal, and spatial analysis of EEG signals. The study by P. Kumar *et al*. (2019) revealed the dynamics of EEG power in the frequency and spatial domains during different emotional states, establishing characteristic patterns of brain activation during the experience of basic emotions.

Transformational changes took place in the development of effective methods for fusing multimodal data. New machine learning algorithms allowed identifying complex nonlinear relationships between different biometric indicators. Experimental studies showed that the use of deep learning methods to combine EEG signals with other physiological indicators could achieve an accuracy of 95-97% in recognising emotional states. Despite significant advances in the field of emotional state recognition, several fundamental problems remained unresolved. The development of an optimal architecture of information systems for processing multimodal biometric data was of paramount importance. Existing approaches to the integration of heterogeneous signals often did not consider their temporal dynamics and nonlinear relationships. The research by Y. Wang *et al*. (2022) emphasised the need to create more flexible models that could adapt to individual characteristics of emotional response. The problem of standardisation and unification of methods of collecting and processing multimodal biometric data remained relevant. The lack of uniform protocols for signal registration and data quality assessment made it difficult to compare the results of different studies. The development of standardised datasets and metrics for evaluating the effectiveness of algorithms was an important task for further research. Special attention should be paid to improving methods for synchronising multimodal signals in real time. Advanced systems often faced the problems of time delays and data loss when simultaneously registering multiple biometric indicators. H. Tang *et al*. (2017) emphasised the need to develop more efficient algorithms for synchronisation and compensation of lost data.

The issue of interpretability of deep learning models for analysing multimodal data remained unresolved. The complexity of neural network architectures made it difficult to understand the principles of decision-making and identify key features that determined the emotional state. Developing methods for visualising and explaining model results was critical for the practical application of emotion recognition systems. The problem of computational complexity of multimodal data processing algorithms also needed to be addressed. Existing methods often required significant computing resources, which made them difficult to use in portable devices and real-time systems. Optimisation of algorithms and development of efficient data compression methods remained relevant research areas.

CONCLUSIONS

The concept of a multimodal approach to the analysis of emotional states based on the integration of EEG signals, peripheral physiological indicators, and behavioural characteristics into a single information system is theoretically substantiated. The idea of a multimodal method to the study of emotional states based on the integration of EEG data, peripheral physiological markers, and behavioural traits into a unified information system has been theoretically substantiated. From 75-80% for single-modality approaches to 90-95% for integrated multimodal systems, the study showed that combining frequency, amplitude, and spatio-temporal features of EEG data with synchronised biometric indicators significantly increases accuracy of emotional state recognition.

Deep neural networks with hybrid architectures provide optimal performance for multimodal integration, especially convolutional networks for spatial pattern recognition in EEG data and recurrent networks for temporal analysis of physiological signals, according analysis of current methods for biometric data processing. Specifically, frequency patterns (enhanced alpha rhythm for positive emotions, increased beta activity for negative states), amplitude characteristics (> 50 μV for positive emotions in frontal leads), and spatial distribution markers (frontal asymmetry of alpha rhythm) comprise the accepted quantitative criteria for emotional state detection. With timestamp synchronising offering exceptional precision (±0.1 ms) and computing efficiency for real-time applications, the study underlined the crucial relevance of signal synchronising techniques. While keeping emotional-specific characteristics in multimodal recordings, adaptive filtering and machine learning techniques were successful for artefact removal.

By customising pre-trained models to fit individual response patterns, transfer learning has shown notable increase (15-20%) in emotional identification accuracy. Early identification of mood disorders and tailored treatment therapies grounded on objective emotional state monitoring present opportunities for pragmatic use in medicine. In educational environments, the established technique enables adaptive learning systems sensitive to students' emotional involvement. The multimodal emotion recognition framework lays a groundwork for emotionally intelligent interfaces with improved user experience in human-machine interaction. Future areas of research should concentrate on developing miniaturised wearable sensor systems for continuous monitoring in real-world environments, improving adaptive algorithms that dynamically adjust to individual users, and increasing the contextual awareness of emotion recognition systems to account for social and environmental factors affecting emotional expression.

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CONFLICT OF INTEREST

None.

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Інтеграція мультимодальних біометричних даних в інформаційну систему для комплексного аналізу емоційних станів на основі електроенцефалограм

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Анотація. Метою цього дослідження була розробка кількісних параметрів для виявлення емоційних станів шляхом комплексного аналізу характеристик сигналів електроенцефалографії (ЕЕГ) у поєднанні з синхронізованими біометричними показниками для покращення точності розпізнавання. Дослідження розглянуло інтеграцію мультимодальних біометричних даних в інформаційну систему для всебічного аналізу емоційних станів, отриманих з ЕЕГ. Була запропонована унікальна методологія, яка об'єднує дані з різних сенсорних систем, що покращує точність розпізнавання емоцій. Аналіз було зосереджено на методах обробки ЕЕГ та інтеграції даних із додаткових біометричних каналів, таких як вирази обличчя, частота серцевих скорочень і шкірно-гальванічна реакція. Було розглянуто алгоритмічні та технологічні аспекти створення системи, а також результати експериментальних досліджень, які підтверджують її ефективність. Особливу увагу приділено гнучкості системи в різних операційних умовах. Алгоритмічні та технологічні аспекти розробки системи були проаналізовані разом із результатами експериментальних досліджень, які підтверджують ефективність таких систем. Мультимодальні системи розпізнавання емоцій мають значний потенціал застосування у різних сферах, зокрема в оцінці психічного здоров'я, діагностиці емоційних станів, адаптивній освіті та створенні систем для вдосконаленої взаємодії людини з машинами. Особлива увага була приділена адаптивності цих систем до різних операційних умов та їх здатності інтегрувати різноманітні біометричні модальності. Ця інтеграція підвищила надійність і точність розпізнавання емоцій. Крім того, прогрес у галузі машинного навчання, особливо у використанні глибоких нейронних мереж, дозволяє проводити комплексний аналіз і синхронізацію мультимодальних даних, що забезпечує високоточне визначення нюансів емоційних станів

Ключові слова: обчислення афекту; фізіологічні сигнали; аналіз нейронних мереж; обробка біосигналів; взаємодія людини з комп'ютером