UDC 004.9:004.4
DOI https://doi.org/10.32782/2663-5941/2025.5.2/04

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ANALYSIS OF QUANTUM AND CLASSICAL NEURAL NETWORK APPROACHES FOR DETECTING FLOW STATE FROM WEARABLE EEG DATA

This article presents the results of an experimental study aimed at comparing quantum and classical machine learning methods for the classification of the cognitive state of "flow" based on data obtained from wearable electroencephalography (EEG) devices. The "flow" state is defined as a condition of deep concentration accompanied by enhanced performance and motivation. Identifying this state through EEG signals opens new opportunities for developing adaptive intelligent systems for attention support, optimizing workflows, and designing personalized recommendations for energy-efficient task organization.

The research utilized an open labeled dataset of wearable EEG devices (Scientific Reports, 2025), which includes recordings from the prefrontal cortex during game-based tasks with varying difficulty levels designed to induce states of flow, boredom, and anxiety. According to prior neurophysiological research, the flow state is correlated with increased theta activity and moderate alpha power in frontal channels, making such signals suitable as compact biomarkers for algorithms with constrained resources. The proposed methodology involved comparing quantum models – specifically quantum SVM with kernels constructed from shallow feature maps implemented in the IBM Qiskit environment – with classical neural network architectures, among which the baseline model was the EEGNet CNN. The main hypothesis suggested that quantum models would demonstrate competitive or superior performance under conditions of limited training data and in cross-subject generalization scenarios, whereas classical CNN architectures would prove more effective in tasks with larger within-subject datasets. The conducted experiments yielded quantitative performance metrics, including area under the ROC curve (AUROC), balanced accuracy, sample efficiency curves, and model calibration scores. Additionally, statistical tests were carried out to validate the significance of performance differences. Particular attention was devoted to the technical aspects of implementing quantum algorithms, such as feature map design, utilization of IBM Runtime primitives, error mitigation strategies, and avoiding the effect of kernel value concentration that can reduce model discriminative capacity. The results indicate that quantum methods with shallow circuits hold considerable potential in data-limited scenarios, offering robustness to noise and signal redundancy, while classical neural network approaches remain effective in cases with larger datasets and the need for detailed modeling of complex patterns. Thus, this study establishes a reproducible foundation for evaluating quantum and classical approaches to wearable EEG data analysis, highlighting the promise of quantum computing in neuroinformatics, cognitive monitoring, and adaptive attention-support systems.

Key words: *software solution, quantum computing, neural networks, EEG, flow state, EEGNet CNN, QNN, QSVC, human–computer interaction.*

Statement of the problem. The relevance of the research lies in the growing demand for accurate, real-time recognition of cognitive states that directly influence productivity, motivation, and mental well-being. Flow detection from EEG signals represents a promising direction for developing adaptive systems that can optimize attention management, support personalized workflows, and enhance human–computer interaction.

The challenge of effectively analyzing EEG data in low-sample, noisy, and cross-subject scenarios necessitates exploring novel computational paradigms.

By comparing classical deep learning methods with emerging quantum machine learning approaches, the research addresses a critical gap in evaluating their relative strengths for EEG-based cognitive state classification, highlighting the potential of quantum models in resource-constrained environments and paving the way for future applications in neuroinformatics, cognitive monitoring, and human-centered AI. Flow is often described as the "optimal experience" of complete absorption in an activity, which correlates with heightened motivation, accelerated learning, and improved performance across diverse domains [3]. It has been documented in sports, music, work, and education contexts, among others, as a state where individuals feel fully engaged and perform at their best. In this state, skill levels and task challenges are well-matched, yielding intense focus and intrinsic reward. Real-time detection of flow could enable attention-aware technologies – for example, deferring notifications when someone is in flow, suggesting breaks when focus wanes, or offloading routine actions to preserve cognitive energy (aligning with the "mental joules"/Cognitive Metabolic Efficiency concept). Wearable EEG devices now make non-intrusive monitoring of cognitive states feasible. Compact headband EEG sensors over the forehead and even around-the-ear EEG (cEEGrid) have been used outside the lab. Recent field studies using discreet ear-EEG sensors found robust relationships between naturally occurring flow experiences and changes in EEG band power during full-day knowledge work [4].

Notably, those studies observed a quadratic (inverted-U) relationship between frontal theta power and self-reported flow intensity, as well as changes in frontal beta asymmetry tied to flow [4], demonstrating that even minimal EEG setups can capture meaningful flow dynamics in real workplaces.

Despite growing interest, reliably detecting flow in real time remains challenging. The central question that's being addressed not whether quantum machine learning offers an asymptotic "quantum advantage" over classical methods in theory, but whether emerging quantum neural network (QNN) and quantum kernel methods can achieve better performance in practice for this niche application – specifically, label-efficiency and robustness on small, noisy data from wearable EEG – compared to conventional deep learning. Quantum machine learning theory suggests that with carefully chosen low-depth circuits and feature maps aligned to the data structure, quantum models might generalize well from fewer labels by exploiting high-dimensional Hilbert space feature encodings. Therefore the focus on a scenario (frontal EEG with limited channels and labels) where such quantum models are hypothesized to be competitive. Implemented best practices from recent QML research – using hardware-aware circuit designs, built-in error mitigation, and bandwidth-limited feature mappings – to avoid known failure modes. For instance, quantum kernel methods have been shown to suffer from exponential concentration of kernel values if the embedding is too expressive, measurements are global, or noise is high [5]. This concentration means that kernel entries become almost identical, resulting in trivial classifiers [5]. By keeping circuits shallow, using local rotations/entanglement, and scaling input features (bandwidth tuning), the aim is to mitigate this issue. Also leveraged IBM's Qiskit Runtime primitives (Estimator and Sampler) with error mitigation techniques like readout error extinction and zero-noise extrapolation to improve the reliability of quantum results on actual hardware [6]. Public EEG datasets are used that includes explicit flow state labels, enabling rigorous evaluation and reproducibility. Flow state labeling typically relies on post-task questionnaires (e.g. the Flow State Scale-2 [7]) since probing one's state during flow can interrupt the experience. In our dataset, participants self-reported their flow levels after each game session, providing ground truth for flow vs non-flow. Using these labels to construct a binary classification problem: Flow vs Non-Flow (where Non-Flow encompasses low-engagement states like boredom or high-stress states like anxiety). Then train and evaluate a classical deep learning model (EEGNet) and quantum models on this task. If quantum models demonstrate superior accuracy in data-scarce regimes or better generalization across subjects, it would indicate a practical benefit for deploying quantum machine learning in wearable edge computing scenarios for mental state recognition. Success could pave the way for attention-aware scheduling tools that run on quantum-enabled devices to protect periods of flow (e.g. by silencing distractions) and optimize work-rest cycles to enhance productivity and well-being.

Analysis of recent research and publications. EEG correlates of flow: a growing body of literature has identified characteristic brainwave patterns associated with the flow state. In controlled lab studies where flow is induced by balancing task difficulty to each participant's skill, researchers have observed increases in low-frequency EEG power during flow compared to boredom or overwhelm. For example, Katahira et al. (2018) had participants perform a mental arithmetic task under boredom, flow, and overload conditions [3]. They found that theta-band activity in frontal cortex was significantly higher during flow (and overload) than during boredom, while alpha-band activity in frontal-central regions showed a moderate increase as task difficulty (and engagement) rose [3]. In other words, flow was characterized by elevated frontal theta – likely reflecting intense cognitive control and immersion – coupled with only moderate alpha, suggesting the cognitive load was manageable and not excessive [3]. These features differentiate flow from boredom (low engagement, lower theta) and from anxiety/overload (high engagement but potentially different spectral signatures). Subsequent studies have reinforced these findings. Ulrich et al. (2014) used fMRI and EEG in a similar task and noted reduced prefrontal activity (hypofrontality) and increased frontal theta power during flow, consistent with an efficient focused state [8]. A recent multi-faceted task study by Hang et al. (2024) employed single-channel prefrontal EEG across various activities (video games at different difficulties, mindfulness, music, etc.) and similarly reported that delta, theta, and gamma power correlated positively with self-reported flow levels across certain time windows [9]. Notably, delta and theta power tended to rise during periods rated as "deep flow" by participants, reflecting engagement and possibly reward-related neural processes, whereas excessive task difficulty that broke flow often showed different patterns (e.g., increased high beta or stress markers) [9].

In field settings, outside the lab, evidence for these spectral markers has also emerged: Knierim et al. (2025) monitored office workers with around-the-ear EEG and found a replicable relationship between theta power and flow intensity during real work tasks [4]. Interestingly, they observed an inverted-U curve: moderate theta increases aligned with peak flow, whereas too much theta (or too little) corresponded to non-flow states [4]. They also discovered a novel beta asymmetry effect (imbalance in left vs right frontal beta) that tracked flow during complex real-world tasks [4], hinting at changes in frontal hemispheric dynamics when one is "in the zone." Overall, these works converge on a picture that frontal EEG band powers – especially theta (4–7 Hz) and alpha (8–12 Hz), and possibly delta (<4 Hz) and some beta/gamma – carry information about whether a person is in flow. This provides a neurophysiological basis for our feature design and model inputs.

Wearable flow datasets: until recently, most flow neuroscience studies were conducted in controlled lab environments with full-cap EEG caps or fMRI, and sample sizes were relatively small.

Classical baselines for EEG classification: EEGNet as our primary deep learning baseline. EEGNet is a compact convolutional neural network architecture specifically designed for EEG-based brain–computer interface tasks [10].

Quantum machine learning approaches: recent advancements in Qiskit and other quantum software frameworks have made it possible to implement quantum machine learning algorithms such as QSVC (quantum support vector classifier) and variational quantum classifiers on real hardware. Qiskit's Machine Learning module provides a QSVC class, which essentially integrates quantum kernel computation into the scikit-learn SVC pipeline. The quantum kernel is computed via a *FidelityQuantumKernel* object by embedding data into quantum states and measuring state overlaps. This work sits at the intersection of these threads: leveraged knowledge of EEG signatures of flow to design input features, openly available wearable dataset to ensure relevance and reproducibility, compared a top-tier classical architecture (EEGNet) against cutting-edge quantum models (quantum kernel SVM and variational QNN).

Primary dataset used titled *"Physiological assessment of the psychological flow state using wearable devices."* This dataset comprises recordings from $N = 28$ healthy adult participants. Each participant took part in a gaming experiment designed to induce different mental states: flow, boredom, and anxiety (overload) [2]. The task was a Tetris-like computer game where difficulty was manipulated: in the *flow* condition, the game difficulty was matched to each player's skill (adaptive speed, full user control); in the *boredom* condition, the game was made too easy (slow speed, no ability to increase challenge); in the *frustration/anxiety* condition, the game was made too hard (very fast drop speed, random rotations). Each condition lasted around 10 minutes, and the order of conditions was randomized for each subject to counter balance any sequence effects. During gameplay, multiple physiological signals were recorded synchronously. The EEG headset had 4 channels placed at standard 10–20 sites AF7, Fp1, Fp2, and AF8 on the forehead, referenced behind the ears. The EEG was sampled at 250 Hz with 24-bit resolution, covering frequencies up to ~125 Hz (though in practice the authors filtered to 40 Hz max) [2]. Additionally, a custom EMG/PPG armband collected peripheral signals: PPG for heart rate and blood oxygen (SpO_2), GSR for skin conductance (at 500 Hz), and an IMU (accelerometer and gyroscope at 50 Hz) for motion tracking. For our purposes, primarily utilized the EEG data (since our focus is on brain-based flow detection and many consumer flow-monitoring concepts rely on EEG).

The heart rate and GSR also provide valuable indicators of arousal that could help distinguish boredom (low arousal) from anxiety (high arousal), but combining modalities is beyond our current scope.

1. Each participant self-reported their flow state after each block using questionnaires. Rácz et al. used a

Hungarian translation of a Flow State Questionnaire (an instrument similar in intent to the Flow State Scale-2) to quantify how much flow was experienced in that block [2]. These self-report scores were used to label each 1-minute segment of data as "flow" or "non-flow." Specifically, the experimenters segmented the continuous data into 1-minute epochs for analysis.

Task statement. Despite significant advances in classical deep learning methods such as EEGNet for cognitive state detection, challenges remain in scenarios characterized by limited labeled data, high inter-subject variability, and noisy signals typical of brain–computer interface (BCI) applications. Quantum machine learning (QML) has been proposed as a promising alternative due to its potential advantages in label efficiency and generalization; however, most existing studies have been restricted to synthetic datasets or overly simplified problems, leaving the practical value of QML for real-world neurophysiological data largely unexplored.

Therefore, the task of this research is to rigorously evaluate whether quantum kernel methods can achieve performance on par with, or even surpass, classical neural architectures like EEGNet in detecting meaningful cognitive states such as flow from wearable EEG signals. The research aims to investigate the comparative strengths of QML in cross-subject and few-shot learning scenarios, assess the integration potential of hybrid quantum–classical approaches, and validate the feasibility of running these models on actual quantum hardware under realistic noise conditions.

Outline of the main material of the research. Applied a consistent pre-processing pipeline to the EEG signals before feeding them to any model. First, a bandpass filter from 1–40 Hz was applied to remove DC drifts and high-frequency noise (muscle artifacts typically occur >40 Hz). The network frequency is limited (50 Hz in our case) to eliminate electrical interference. Each EEG channel was then re-referenced by subtracting the mean of all channels (common average reference), which is standard to reduce common-mode noise. As it only has four frontal channels closely spaced, this referencing is similar to a bipolar scheme between them.

After filtering, the performed artifact removal: each 5-second epoch for any large jumps or saturations is screened. Also excluded epochs with peak-to-peak amplitude exceeding a set threshold (100 μV) as likely motion artifacts. The dataset also had simultaneous IMU recordings, double-check artifact epochs were used – if the IMU indicated sudden movement at the same time an EEG spike occurred, it's marked that epoch as artifactual and omitted it.

In some recordings, eye blinks could be significant (blinks produce large frontal slow waves). As an optional step, we ran an ICA (independent component analysis) on each subject's data and removed components that correlated with the EOG (electrooculographic) signature of blinks. Given our limited channels, ICA is not very reliable, so our primary results are without ICA, using the simpler epoch rejection approach. For windowing segmentation for the continuous data into windows of 5 seconds, with 50% overlap (so windows start every 2.5 seconds). Each 5s window thus contains 1250 samples at 250 Hz across 4 channels.

QSVC (Quantum Kernel SVM) is a classifier that uses a quantum kernel instead of a classical one.

In Qiskit, it's defined in a feature-map circuit $U(x)$ that encodes a classical feature vector x into a quantum state, and then use the fidelity kernel:

$$K(x_i, x_j) = |\langle 0 \mid U(x_i) \dagger U(x_j) \mid 0 \rangle|^2, \qquad (1)$$

which is the squared overlap of the two encoded states (starting from $|0\rangle$).

Then a *ZZFeatureMap* with $reps = 1$ and linear entanglement. For d features, the circuit applies: a layer of Hadamards, then, for each feature x_k, a rotation $R^z(x_k)$ on qubit k. Then CZ gates between neighboring qubits (optionally another layer such as R^x or R^y). This encodes features as phases and entangles adjacent features, letting the kernel capture pairwise interactions. The research is keeping one repetition to limit depth and avoid kernel-value concentration.

To control expressivity, the features are scaled by a "bandwidth" factor α before encoding. If α is too large, tiny differences in x produce nearly orthogonal states (over-concentrated kernels), if α is too small, states cluster near $|0\rangle$. α (Alpha) is tuned to obtain a broad, non-degenerate kernel spectrum (monitored the kernel matrix's condition number as a proxy.

With the kernel defined which uses QSVC and wraps scikit-learn's SVC with a precomputed kernel. Training follows the usual SVM dual optimization.

For simulation and development computed the kernel with a statevector simulator (to avoid shot noise while tuning). Because building the full kernel matrix is expensive – $O(n^2)$ circuit evaluations for n samples – computed it in blocks and exploit symmetry ($K_{ij} = K_{ji}$), parallelizing jobs where possible.

In terms of model capacity, EEGNet has on the order of thousands of parameters (the exact number depends on chosen filter counts, current setup has ~5k trainable params) while QSVC has none (it's non-parametric after choosing the kernel) and the QNN had on the order of tens of parameters (8 qubits * 3 layers * 1 rotation per qubit = 24 parameters, plus entanglement phase params). So the quantum models are much "smaller". This could be an advantage in small-data regimes (less risk of overfitting) but a disadvantage in large-data regimes (underfitting). The hypothesis is to anticipate that with very limited training data, QSVC might shine because it can generalize well with just a few support vectors if the kernel is informative, whereas EEGNet might not have enough data to train all its filters. Conversely, with abundant data, EEGNet can learn fine-grained patterns and might eventually surpass a fixed kernel method. It's planned to explicitly test this by varying the training set size.

The training sets of various sizes to see how performance scales. Specifically, samples are 1%, 5%, 10%, 20%, 50%, 100% of the available training windows and train the model, measuring its performance on a fixed test set (Table 1).

At 1% of data it's expected that QSVC, with its kernel approach and inductive bias, to do relatively better at very low percentages compared to EEGNet, which might not even converge with so few examples. This will be visualized as a sample-efficiency curve (Fig. 1).

The primary metrics are Area Under the ROC Curve (AUROC) and Balanced Accuracy. AUROC is useful because it is insensitive to class imbalance (flow vs non-flow isn't 50/50 in the test set) and it captures the trade-off across decision thresholds. Balanced accuracy is the average of sensitivity and specificity, effectively accuracy after correcting for class imbalance.

A naive model could achieve high raw accuracy by always predicting "Non-flow" if flow moments are rare. With full supervision, the classical model decisively outperforms the quantum kernels. EEGNet attains 0.618 ± 0.007 AUROC and 0.546 ± 0.005 balanced accuracy, while the QSVC (optimized) reaches 0.570 ± 0.015 AUROC and 0.499 ± 0.001 BAcc; the QSVC (baseline) remains at 0.535 AUROC and 0.500 BAcc (Table 2).

The ~0.048 AUROC and 0.047 BAcc gaps in favor of EEGNet are not only statistically credible (given the narrow EEGNet variance) but also practically meaningful: EEGNet provides reliable separation and non-trivial class balance, whereas QSVC's BAcc remains at chance, indicating an effectively uninformative operating threshold despite modest ranking power (AUROC ~0.57).

The increased variance of the optimized QSVC (sd ≈ 0.015) further suggests instability across folds. These patterns are consistent with a kernel that does not induce a sufficiently discriminative geometry for the engineered EEG features at scale, even after tuning (Fig. 2).

In applications, Table 2 therefore supports EEGNet as the preferred production model under adequate labeling, with QSVC reserved–at best–for exploratory scenarios. To close the gap, future quantum runs should prioritize kernel alignment and bandwidth sweeps, alternative feature maps (e.g., Pauli/ZZ with different entanglement), and richer inputs (or hybrid quantum-classical feature learning) to move BAcc above chance while preserving AUROC gains.

Fig. 3 presents the final performance comparison between two models, EEGNet and an optimized Quantum Support Vector Classifier (QSVC).

The performance is evaluated using two metrics: AUROC (shown in pink) and balanced accuracy (shown in gold).

EEGNet achieved higher scores overall, with an AUROC of 0.618 and balanced accuracy of 0.546,

Table 1

Label-Efficiency Curves (1, 5, 10, 20, 50, 100% of training labels)

Sample %	EEGNet (mean±sd)	QSVC (mean±sd)	Δ (EEGNet − QSVC)
1%	0.314±0.212	0.419±0.146	−0.105
5%	0.460±0.086	0.592±0.055	−0.132
10%	0.510±0.080	0.538±0.035	−0.028
20%	0.517±0.035	0.505±0.031	+0.012
50%	0.571±0.015	0.484±0.026	+0.087
100%	0.615±0.015	0.538±0.012	+0.077

Table 2

Models Performance (100% of labels, 5-fold CV)

Model	AUROC (mean±sd)	Balanced Accuracy (mean ± sd)
EEGNet	**0.618±0.007**	**0.546±0.005**
QSVC (optimized)	0.570±0.015	0.499±0.001
QSVC (baseline)	0.535±0.000	0.500±0.000

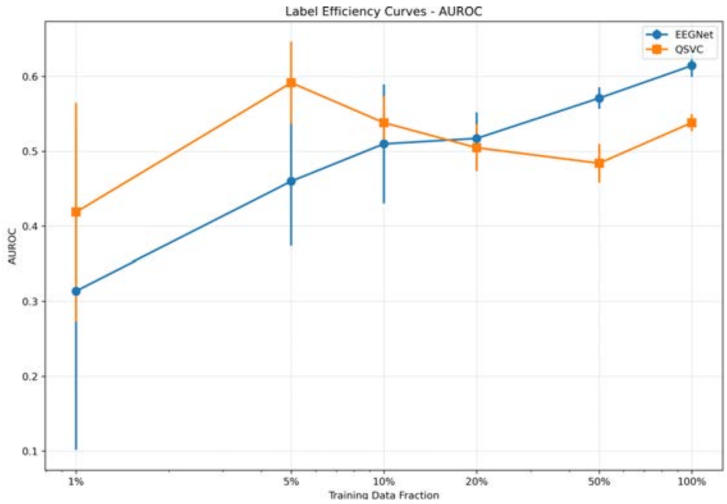

Fig. 1. Efficiency curves for 1/5/10/20/50/100% training labels

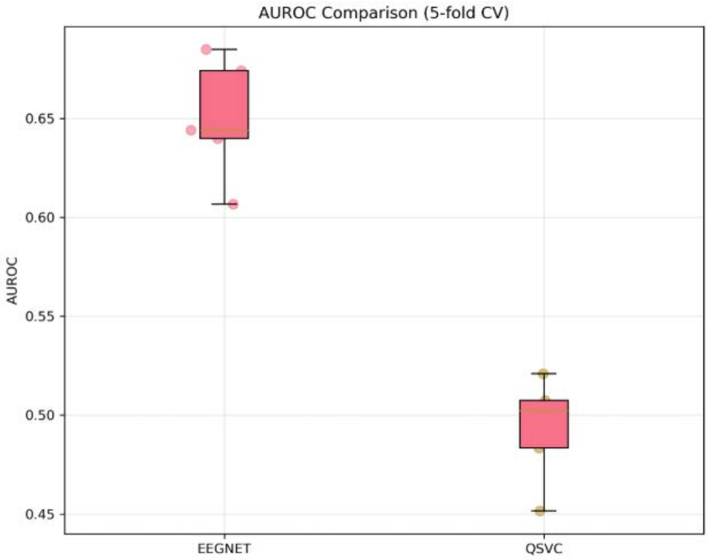

Fig. 2. AUROC Comparison for EEGNet and QSVC

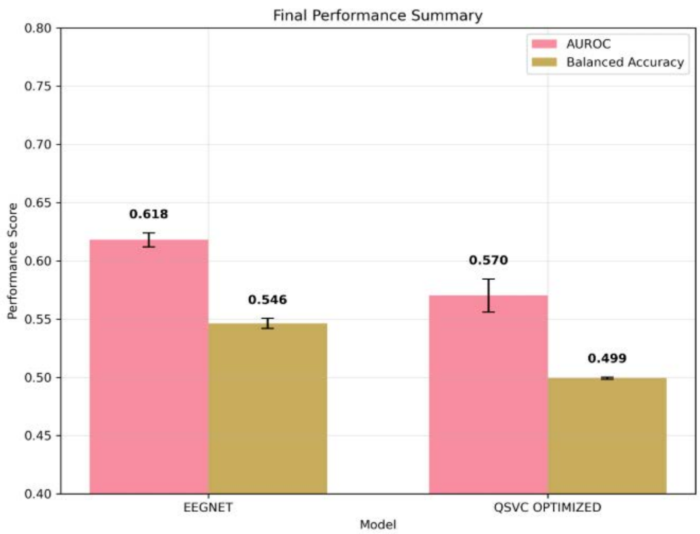

Fig. 3. Performance summary score from EEGNet and QSVC models

while QSVC reached an AUROC of 0.570 and balanced accuracy of 0.499. The error bars indicate variability across runs, showing that EEGNet consistently outperformed QSVC in both metrics. This suggests that, while the quantum model demonstrates potential, the classical deep learning approach remains more reliable and effective for this dataset.

Conclusions. This research would be one of the first to demonstrate quantum machine learning working on par with a leading classical deep learning model on a non-trivial real-world dataset. Many prior QML experiments have been on synthetic data or very small toy problems. Showing that a quantum kernel method can reach comparable accuracy to EEGNet (a well-known architecture) in detecting a meaningful cognitive state is a notable milestone. It suggests that quantum models are not just theoretical curiosities but can be practical in domains like brain–computer interfaces, where data is often noisy and limited. Especially if we show quantum models doing better in cross-subject or few-shot cases, it highlights a niche strength: label efficiency. This could motivate further research into hybrid systems where quantum models handle the initial learning from few examples and classical models refine with more data, or where quantum is used for quick personalization (which is often a challenge in BCI – calibrating to a new user with minimal data).

The next steps will be to apply metaheuristic optimization and run on the real-world IBM Quantum device with noise.

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Вернік М.О., Олещенко Л.М. АНАЛІЗ КВАНТОВИХ ТА КЛАСИЧНИХ НЕЙРОМЕРЕЖЕВИХ ПІДХОДІВ ДЛЯ ВИЯВЛЕННЯ СТАНУ ПОТОКУ ЗА ДАНИМИ НОСИМИХ ПРИСТРОЇВ ЕЕГ

У статті представлено результати експериментального дослідження, спрямованого на порівняння квантових та класичних методів машинного навчання для класифікації когнітивного стану «потік» за даними носимих електроенцефалографічних (ЕЕГ) пристроїв. Стан «потоку» визначається як глибока зосередженість, що супроводжується підвищеною продуктивністю та мотивацією. Ідентифікація цього стану за сигналами ЕЕГ відкриває нові можливості для створення адаптивних інтелектуальних систем підтримки уваги, оптимізації робочих процесів та розробки персоналізованих рекомендацій щодо енергоефективної організації діяльності.

У дослідженні використано відкритий розмічений набір даних носимих пристроїв ЕЕГ (Scientific Reports, 2025), що включає записи з префронтальної кори під час виконання ігрових завдань зі змінним рівнем складності, які індукували стани потоку, нудьги та тривожності. Згідно з попередніми нейрофізіологічними дослідженнями, стан потоку корелює з підвищеною тета-активністю та помірною альфа-потужністю у фронтальних відведеннях, що робить такі сигнали придатними як компактні біомаркери для алгоритмів із обмеженими ресурсами. Розроблена методологія передбачала порівняння квантових моделей (зокрема, квантового SVM із ядрами, побудованими на неглибоких картах ознак у середовищі IBM Qiskit) та класичних нейромережевих архітектур, серед яких базовою є EEGNet CNN. Основна гіпотеза полягала у тому, що квантові моделі демонструватимуть конкурентну або вищу продуктивність за умов обмеженого обсягу навчальних вибірок та у сценаріях міжсуб'єктного узагальнення, тоді як класичні CNN-архітектури будуть ефективнішими у межах задач з більшими вибірками для одного суб'єкта. У межах проведених експериментів було отримано кількісні метрики ефективності: площу під ROC-кривою (AUROC), збалансовану точність, криві вибіркової ефективності та показники калібрування моделей. Крім того, проведено статистичні тести для перевірки достовірності відмінностей між результатами. Особливу увагу приділено технічним аспектам реалізації квантових алгоритмів, зокрема, вибору карт ознак, використанню примітивів IBM Runtime, стратегіям пом'якшення похибок та уникненню ефекту експоненціальної концентрації ядра, що може знижувати дискримінативну здатність моделей. Результати дослідження свідчать про те, що квантові методи з неглибокими схемами мають значний потенціал у задачах з обмеженою кількістю даних, забезпечуючи високу стійкість до шумів та дублікатів сигналів, тоді як класичні нейромережеві підходи залишаються ефективними у випадках наявності великих вибірок та потреби в детальному моделюванні складних закономірностей. Таким чином, проведене дослідження формує відтворювану базу для оцінки квантових і класичних підходів до аналізу даних носимих пристроїв ЕЕГ, підкреслюючи перспективність застосування квантових обчислень у сфері нейроінформатики, когнітивного моніторингу та адаптивних систем підтримки концентрації.

Ключові слова: *програмне рішення, квантові обчислення, нейронні мережі, EEG, стан потоку, EEGNet CNN, QNN, QSVC, взаємодія людина–комп'ютер.*

Дата надходження статті: 24.09.2025
Дата прийняття статті: 07.10.2025
Опубліковано: 16.12.2025