# A New Algorithm for Automated Diagnosis of Delayed Cerebral Ischemia in Video-EEG Monitoring Data

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**Abstract**

The paper proposes a new algorithm for automated diagnosis of delayed cerebral ischemia in video-EEG monitoring data. The algorithm uses the indicator of the delayed cerebral ischemia which is the number of epileptiform discharges per hour over a sufficiently long observation interval. It combines a detector of epileptiform discharges and a new motion artifact detector. The epileptiform discharge detection algorithm analyzes the cross-correlation function of EEG signals with a reference fragment pre-selected by medical experts. In the motion artifact detection algorithm, we propose to calculate the mobility index from blurred edge maps of the region of interest, which are less sensitive to fluctuations in illumination level. As an indicator of mobility, we use the variation of information, which characterizes the informational difference of video frames. We obtained preliminary results that confirm the effectiveness of the proposed algorithm. The developed algorithm for early automated diagnostics of delayed cerebral ischemia provides sensitivity equal to 0.9 and specificity equal to 0.79. The obtained quality measures correspond to the quality level of known methods for diagnosing delayed cerebral ischemia based on EEG signals. At the same time, the accuracy of detecting motion artifacts is 0.9, and the F1 score is 0.93. The detection algorithm for epileptiform discharges provides sensitivity of 0.95 and specificity of 0.85.

## 1. Introduction

One of the effective methods for early diagnosis of delayed cerebral ischemia (DCI) in subarachnoid hemorrhage (SAH) is the analysis of electroencephalogram (EEG) signals (Kondziella, 2015), (Rosenthal, 2018), and (Kasi, 2025). Existing EEG monitoring systems provide real-time EEG recording with distortions caused by instrumental artifacts and artifacts of the patient's vital activity. To identify and exclude time intervals with artifacts caused by the patient's vital activity and care by medical staff, it is advisable to analyze video recordings synchronous with the EEG. The article (Murashov, 2023) presented an automated system that made it possible to detect, classify and predict in real time the indicators of delayed ischemia after subarachnoid hemorrhage based on long-term video-EEG monitoring data. To detect ischemia indicators, the ridges of the spectrograms of wavelet transforms of EEG signals were analyzed. Artifacts caused by the patient's vital activity and care by medical personnel were fixed by a threshold detector using the optical flow value, which was calculated from video recording frames. However, the calculation and analysis of wavelet transform spectrogram ridges requires high computational costs. Additionally, the optical flow used to detect motion artifacts may be distorted by changes in illumination in the intensive care unit. Therefore, it is necessary to develop a motion artifact detector that reduces the sensitivity of the detector to the above-mentioned interference without significantly increasing computational costs. The works (Kim, 2022) and (Zheng, 2022) proposed a new indicator of the DCI, which is the number of epileptiform discharges (ED) per hour. It has been shown that a sufficiently large number of ED per hour over a long period of time (more than 3 hours) indicates a high risk of developing DCI. The article (Obukhov, 2024) proposed a new algorithm for automatic detection of epileptiform spike wave discharges (SWD) based on the cross-correlation of the EEG and the SWD graphic pattern template.

This paper proposes a new algorithm for automated diagnosis of delayed cerebral ischemia in video-EEG monitoring data based on the indicator of the DCI presented in (Kim, 2022) and (Zheng, 2022), algorithm for automatic detection of epileptiform discharges developed in (Obukhov, 2024), and a new motion artifact detector.

## 2. Algorithm for Diagnosing Delayed Cerebral Ischemia

The algorithm for diagnosing ischemia is based on EEG analysis in order to detect signal fragments of a certain shape, specified as a reference EEG fragment. A diagnostic decision to detect an indicator of DCI is made if the number of ER per hour over a sufficiently long observation interval exceeds a predefined threshold value.

The algorithm for detecting artifacts caused by the patient's vital activity and the work of medical personnel is based on the analysis of the magnitude of the variation of information, which is calculated from adjacent frames of video recordings. Using the EEG analysis algorithm, we predict the possibility of ischemia. By analyzing the information differences in video frames, we find motion artifacts and exclude events that can be falsely taken for epileptiform discharges and distort the DCI

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indicator. Below, we will consider the components of the proposed algorithm for diagnosing delayed cerebral ischemia.

### 2.1 Detection of Epileptic Discharges

The epileptiform discharge detection algorithm proposed in (Obukhov, 2024) analyzes the cross-correlation functions of EEG signals with a reference fragment pre-selected by an expert physician, consisting of a spike-wave discharge with a sharp negative spike (peak) with a large amplitude and a subsequent slow positive wave. The algorithm detects an epileptiform discharge if the patient's EEG fragment has the following features: (a) the peak amplitude should exceed 40 μV; (b) the correlation function should change sign when moving from the peak to the wave; (c) the value of the maximum of the correlation function of the ED peak should be greater than 0.4; (d) the half-width of the peak should not exceed 100 ms; (e) the area under the wave should be greater than the area under the peak of the EEG signal; (f) in the interval of 40 ms there should be two or more peaks of the correlation function in different EEG channels.

### 2.2 Detection of Motion Artifacts

In (Murashov, 2023), we used the optical flow value in the region of interest (ROI) to detect motion artifacts. However, this mobility indicator is sensitive to changes in the illumination level in the room where the recording was carried out. A number of methods for computing optical flow using operators that compute invariant local descriptors have been presented in the literature, see for example the review (Trinh, 2019). The analysis of these descriptors showed that local descriptors detect edges and demonstrate effectiveness on various test image databases. In the following subsections, a new motion artifact detection algorithm will be proposed that is less sensitive to scene illumination variations and simpler in terms of computational costs than the one used by the authors earlier in their work (Murashov, 2023).

**2.2.1 Information-Theoretic Indicator of Mobility:** Taking into account the analysis of known local descriptors, to improve the reliability of motion detection in a frame, we propose to calculate the mobility index from blurred edge maps of the region of interest, which are less sensitive to fluctuations in illumination levels.

Let the region of interest of frame number $k$ of the video recording be described by the mapping

$$U_k : \mathbb{Z}^2 \to \mathbb{Z}.$$

The edge map of the region of interest of the frame with number $k$, blurred by a Gaussian kernel, is represented by the relation:

$$I_k(x, y) = G * \vartheta(U_k(x, y)), \quad (1)$$

where $I_k(x, y)$ = brightness level of the blurred edge map at a point with spatial coordinates $x$ and $y$

$\vartheta(\ )$ = edge detector operator

$G$ = Gaussian filter kernel

$*$ = convolution operation

Figure 1 shows the ROI of one of the frames, and the corresponding blurred edge map is shown in Figure 2.

Figure 1. The region of interest of one of the frames of the video recording.

Figure 2. A Gaussian blurred edge map of the ROI of the video frame shown in Figure 1.

In (Murashov, 2023), the optical flow value in the region of interest was used as an indicator of mobility. Computing optical flow requires significant computational effort. Therefore, we propose to use information variation (Meila, 2007) as an indicator of mobility, which requires less computation. The variation of information in the problem under consideration is a measure of the difference in the edge maps of video frames. To use the information-theoretic measure of frame difference, it is necessary to represent the procedure for processing video recordings in the form of an information channel.

Let the brightness levels of pixels in the region of interest of successive frames of a video recording be described by random variables $I_k$ and $I_{k-1}$ with values $i_k$ and $i_{k-1}$. We will consider the regions of interest of consecutive frames as the input and output of some information channel:

$$I_k = \varphi(I_{k-1}) + \eta_{k-1}, \quad (2)$$

where $I_{k-1}$ = channel input

$I_k$ = channel output

$\varphi_k(\ )$ = transformation function

$\eta_k$ = noise

Variables $I_{k-1}$ and $\eta_k$ are independent. Variation of information in work (Meila, 2007) is defined as follows:

$$VI\left(I_k, I_{k-1}\right) = 2H\left(I_k, I_{k-1}\right) - H\left(I_k\right) - H\left(I_{k-1}\right), \quad (3)$$

where $H\left(I_k, I_{k-1}\right)$ = joint entropy of edge maps $I_k$ and $I_{k-1}$ of regions of interest of frames with numbers $k$ and $k-1$.
$H\left(I_k\right)$, $H\left(I_{k-1}\right)$ = marginal entropies of the edge maps of the ROIs $I_k$ and $I_{k-1}$, respectively

When detecting events, smoothing of the mobility index is performed using the Kalman-Bucy filtering algorithm:

$$\hat{VI}\left(I_k, I_{k-1}\right) = F_K\left(VI\left(I_k, I_{k-1}\right)\right), \quad (4)$$

where $\hat{VI}\left(I_k, I_{k-1}\right)$ = smoothed $VI\left(I_k, I_{k-1}\right)$
$F_K(\,)$ = Kalman filter operator

To make a decision about the detection of an artifact, we will use a classifier with a quadratic separating function (Duda, 2001), which we applied earlier in (Murashov, 2023a):

$$Event\hat{VI} = \begin{cases} 1, \; if \; g\left(k\right) > 0 \; and \; \; k - k_0 \geq M, \\ 0, \; if \; g\left(k\right) \leq 0 \; \; or \; k - k_0 < M, \end{cases} \quad (5)$$

$$g\left(k\right) = -\left(\frac{1}{2\sigma_1^2} - \frac{1}{2\sigma_2^2}\right)\hat{VI}^2\left(I_k, I_{k-1}\right) + \left(\frac{\mu_1}{\sigma_1^2} - \frac{\mu_2}{\sigma_2^2}\right)\hat{VI}\left(I_k, I_{k-1}\right) - \left(\frac{\mu_1^2}{2\sigma_1^2} - \frac{\mu_2^2}{2\sigma_2^2}\right), \quad (6)$$

where $Event\hat{VI}$ = event indicator
$g\left(k\right)$ = separating function
$\mu_1$, $\mu_2$, $\sigma_1$, $\sigma_2$ = means and standard deviations of the mobility index in fragments of a video sequence with low and high scene dynamics, respectively
$k_0$ = frame number from which the inequality $g\left(k\right) > 0$ is satisfied
$M$ = the length of the frame sequence required to make a decision about detecting an artifact

Applying such a classifier is due to the characteristics of the medical equipment available in the clinic. The spatial position of the camera and, accordingly, the field of view and region of interest may change depending on the actions of medical personnel associated with medical procedures and patient care. In this case, reconfiguring the classifier specified by formulas (5) and (6) is reduced to calculating the parameters $\mu_1$, $\mu_2$, $\sigma_1$, and $\sigma_2$ from test video recordings of scenes with low and high levels of activity in the region of interest for a new camera position. This operation is not difficult and does not take much time.
Figure 3 shows graphs of two indicators of mobility of the region of interest, namely optical flow $\hat{J}$ (see (Murashov, 2023)) and variation of information $\hat{VI}$, constructed from a fragment of a patient's video recording. The graphs also show the results of detecting motion artifacts using $\hat{J}$ and $\hat{VI}$ values (curves $Event\,\hat{J}$ and $Event\hat{VI}$). These graphs show that interframe variation of information, despite a slightly lower dynamic range, represents the mobility of the region of interest as well as optical flow, and can be used in a motion artifact detector.

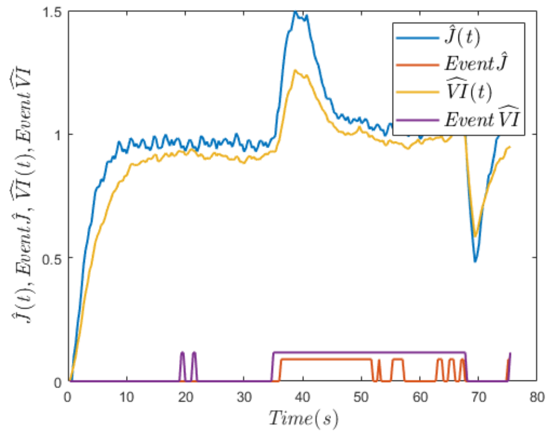


Figure 3. Graphs of optical flow $\hat{J}$, variation of information $\hat{VI}$, and motion artifact detection indicators $Event\,\hat{J}$ and $Event\hat{VI}$, constructed from a fragment of the patient's video recording.

**2.2.2 Estimation of the Computational Complexity of Mobility Indicator:** The computational complexity of one iteration of the Lucas-Kanade algorithm (Lucas, 1981), used to compute the optical flow in (Murashov, 2023), is $O\left(n^2N + n^3\right)$ (Baker, 2004), where $n$ is the number of warp parameters and $N$ is the number of pixels in the region of interest.
To calculate the variation of information, it is necessary to perform the operations of forming a two-dimensional and two one-dimensional histograms describing the brightness distributions in the edge maps $I_k$ and $I_{k-1}$, and calculating the joint and two marginal entropies.
Let the pixels of the brightness difference maps have $l$ brightness gradations. Forming one histogram requires performing $N$ summation and $N$ division operations. To calculate the joint entropy $H\left(I_k, I_{k-1}\right)$, $l^2$ multiplication operations, $l^2 - 1$ summation operations, and $l^2$ logarithm operations are required. Calculating marginal entropy requires $l$ multiplications, $l-1$ summations, and $l^2$ logarithm operations. In total, the calculation of $VI\left(I_k, I_{k-1}\right)$ requires $2N + \left(4m+2\right)l^2 + 2(4m+2)l$ operations, where $m$ is the number of terms of the logarithm expansion series. Taking into account the rules for estimating the complexity of an algorithm (Arora and Barak, 2009), we find that the complexity of calculating the variation of information is equal to $O\left(N + ml^2\right)$. It is shown that for the used sizes of the region of interest ($N > 7\times10^5$ pixels), $n = 2$, $n = 5$ and $l = 256$,

the use of information variation as an indicator of mobility is more preferable compared to the value of optical flow.

### 2.3 Algorithm for Detecting the Indicator of Delayed Cerebral Ischemia

Based on the algorithms described in subsections 2.1 and 2.2, we propose a DCI detection algorithm based on the indicator, which takes into account the number of epileptiform discharges per hour. EEG signals and video recordings are analyzed synchronously. The algorithm includes the following steps:

1) resetting the ED counters $C_{ED} = 0$ in the left and right hemispheres of the brain and resetting the time counter $C_t = 0$;

2) analysis of EEG signals in the channels of the left and right hemispheres of the brain: checking conditions (a) - (f) (see subsection 2.1) and making a decision on the detection of an epileptiform discharge at time $t$ corresponding to frame number $k$ of the video recording;

3) analysis of the regions of interest of video recording frames with numbers $k$ and $k-1$, calculation of the value of the mobility index $\hat{VI}\left(I_k, I_{k-1}\right)$ (see formulas (1) - (4)) and verification of conditions (5), (6) (see subsection 2.2);

4) if at time $t$ conditions (a) – (f) of the ED detection algorithm and (5) and (6) of the motion detector in the region of interest are met, then a decision is made to detect an artifact caused by the patient's vital activity or the work of medical personnel;

5) if conditions (a) - (f) are met, but conditions (5) and (6) are not met, then a decision is made that an epileptiform discharge is detected, and the counter $C_{ED}$ is increased by one: $C_{ED} = C_{ED} + 1$;

6) checking the time counter and comparing the value of the ED counter with the threshold $T$: if the value of the time counter exceeds 1 hour $C_t > 1$ and the ED counter value exceeds the threshold $C_{ED} > T$, then a decision is made about the appearance of the DCI indicator, go to step 1);

7) the time counter value does not exceed 1 hour $C_t \le 1$, go to step 2).

A diagnostic decision to detect DCI is made if the number of EDs per hour over a sufficiently long observation interval exceeds the threshold value $T$.

The flow chart of the DCI indicator detection algorithm is shown in Figure 4. The next section will describe a computational experiment that confirms the functionality of the proposed algorithm.

## 3. Computational Experiment

To evaluate the effectiveness of the developed DCI diagnostic algorithm, we conducted a computational experiment. The experiment included three stages. In the first stage, we tested a new algorithm for detecting motion artifacts based on the information-theoretic indicator of the mobility of the region of interest and compared it with the algorithm previously used in the work (Murashov, 2023). At the second stage, the quality of epileptiform discharge detection was assessed taking into account the detection of artifacts caused by the patient's vital activity or the work of medical personnel. At the third stage, the characteristics of the developed algorithm for diagnosing DCI as a whole were assessed.

The calculations were performed on a computer with an Intel CORE i7-9750H processor with a clock frequency of 2.60 GHz and 32 GB of RAM.

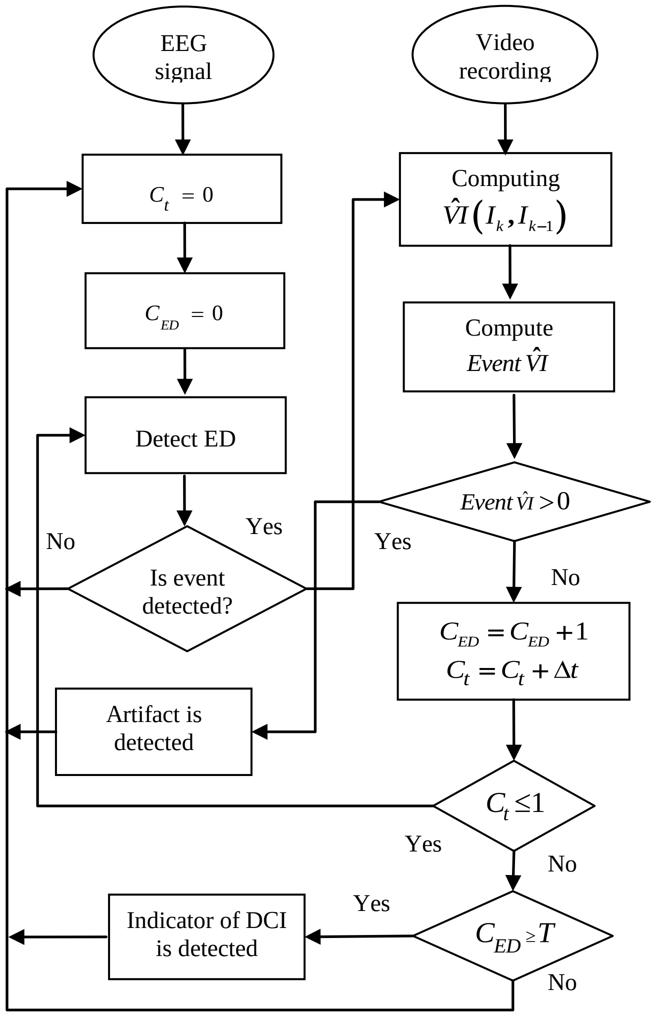


Figure 4. Flowchart of the algorithm for detecting delayed ischemia indicator.

### 3.1 Testing the Information-Theoretic Mobility Indicator

To test a new indicator of mobility, video recordings of three patients with a duration of 24, 31 and 27 hours were used synchronous with EEG signals. We examined 192 fragments that recorded events corresponding to the epileptiform discharge patterns found in the EEG signals. These fragments were tested using two algorithms with different mobility indices. The first algorithm used the value of variation of information between the blurred edge maps of the ROIs of two consecutive frames. In the second algorithm, we used the magnitude of the optical flow in the region of interest as an indicator of mobility.

The detection results are shown in Table 1. Based on the data in Table 1, the quality measures of motion artifact detection are calculated and presented in Table 2. The data presented in Table 1 show that the algorithm with the mobility indicator in the form of variation of information produced a greater number of true positive and false positive, but fewer false negative decisions. This resulted in higher sensitivity, accuracy and F1-score values compared to those of the optical flow-based algorithm (see Table 2).

| Detection results | Number of detections | |
|---|---|---|
| | Optical flow-based | *VI*-based |
| True positive | 99 | 111 |
| True negative | 67 | 63 |
| False positive | 1 | 5 |
| False negative | 25 | 13 |

Table 1. Results of motion artifact detection by two algorithms with different mobility indices.

| Quality measure | Detector results | |
|---|---|---|
| | Optical flow-based | *VI*-based |
| Precision | 0.99 | 0.96 |
| Sensitivity | 0.8 | 0.9 |
| Specificity | 0.99 | 0.93 |
| Accuracy | 0.86 | 0.9 |
| F1 score | 0.88 | 0.93 |

Table 2. Quality measures of detectors with different mobility indices.

### 3.2 Assessing the Quality of Localization of Epileptiform Discharges in EEG Signals Taking into Account the Motion Artifacts

The quality of localization of epileptiform discharges was assessed using the same video-EEG monitoring data as testing the motion artifact detector. A total of 168 events were identified in the EEG signals. Detection of motion artifacts was performed on time intervals of 25 seconds, centered relative to the time moments at which epileptiform discharges were localized in the EEG signals. In the video recording synchronized with the EEG, 68 artifacts were correctly found, 12 artifacts were missed, and 4 were found incorrectly. The obtained results of the ED detector operation are presented in Table 3.

| Patients | True positive | True negative | False positive | False negative |
|---|---|---|---|---|
| Patient 1 | 8 | 19 | 0 | 1 |
| Patient 2 | 27 | 29 | 2 | 3 |
| Patient 3 | 49 | 20 | 10 | 0 |
| Total | 84 | 68 | 12 | 4 |

Table 3. Results of the epileptiform discharge detector operation taking into account motion artifacts.

Table 4 presents the quality measures of the epileptic discharge detector calculated using the data from Table 3. The data in Table 4 shows that the proposed algorithm for detecting epileptic discharges demonstrates sensitivity, accuracy and F1 score values acceptable for diagnosis (more than 90%).

| Quality measure | Value |
|---|---|
| Precision | 0.88 |
| Sensitivity | 0.95 |
| Specificity | 0.85 |
| Accuracy | 0.9 |
| F1 score | 0.91 |

Table 4. Measures of ER detector quality taking into account motion artifacts.

### 3.3 Testing the DCI Detection Algorithm

To test the proposed algorithm, long-term (more than 24 hours) video-EEG monitoring data from 23 patients were studied, including 14 without the development of DCI after SAH and 9 patients with DCI after SAH. As an indicator of DCI, we used the hourly number of EDs detected in EEG signals over a long time interval (more than 6 hours) excluding artifacts caused by patient movement and medical personnel.

To decide whether a DCI indicator is detected, a threshold value $T$ of the number of EDs per hour must be set. In the experiment, we used three threshold values (10, 15 and 20). In the analysis of clinical records, we assessed the accuracy, specificity and sensitivity of the automatic DCI detection algorithm at the selected threshold values and at a cluster duration of the hourly number of epileptiform discharges in the EEG equal to six hours. The obtained results are presented in Table 5.

| Threshold number of ED per hour | Measures | | |
|---|---|---|---|
| | Sensitivity | Specificity | Accuracy |
| 10 | 0.9 | 0.79 | 0.83 |
| 15 | 0.9 | 0.79 | 0.83 |
| 20 | 0.78 | 0.79 | 0.75 |

Table 5. Measures of the quality of the algorithm for detecting the DCI indicator for a given duration of clusters of the hourly number of ED.

From the data in Table 5 it can be seen that with an increase in the threshold value from 15 to 20 epileptic discharges per hour, the sensitivity and accuracy decrease from 0.9 to 0.78 and from 0.83 to 0.75, respectively. At the same time, the specificity for all threshold values does not change and is equal to 0.79. According to Table 5, we can conclude that a threshold value in the range of 10 – 15 EDs per hour is preferable.

The quality measures obtained in the experiment correspond to the results of DCI detection from EEG signals published in the literature. For example, in the work (Rosenthal, 2018), the authors achieved a sensitivity level of 91 and 95 percent, and a specificity of 83 and 77 percent for different groups of patients. The authors of the work (Zheng, 2022) obtained sensitivity values of 0.69 and 0.76 and specificity of 0.67 and 0.59 for different periods after SAH. In the work (Santana, 2024), the authors reported that based on the results of six studies, levels of the pooled sensitivity and pooled specificity were equal to 0.74 and 0.78, respectively.

## 4. Conclusions

A new algorithm for automated diagnostics of delayed cerebral ischemia based on video-EEG monitoring data has been developed. To make a diagnostic decision, the DCI indicator proposed in (Kim, 2022) is used. The indicator is calculated using the epileptiform discharge detection algorithm developed by the authors in (Obukhov, 2024) and a new motion artifact detector based on an information-theoretical measure of activity in the region of interest. To evaluate the effectiveness of the proposed algorithm, a computational experiment was conducted. The obtained preliminary results showed that the values of quality measures (sensitivity is 0.9 and specificity is 0.79) of the developed algorithm for automated diagnosis of DCI after SAH correspond to the quality level of known algorithms for detecting DCI from EEG signals. The experimental results also showed that the accuracy of motion artifact detection is 0.9, and the F1-score is 0.93. The algorithm for detecting epileptiform discharges with artifact exclusion provides sensitivity equal to 0.95 and specificity equal to 0.85. Further research will be aimed at improving the quality of diagnosis by using additional DCI features.

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## References

Arora, S., Barak, B., 2009. *Computational Complexity: A Modern Approach*. Cambridge University Press, Cambridge.

Baker, S., Matthews, I., 2004. Lucas-Kanade 20 Years On: A Unifying Framework. *Int. J. of Computer Vision*, 56, 221–255. https://doi.org/10.1023/B:VISI.0000011205. 11775.fd

Duda, R.O., Hart, P.E., Stork, D., 2001. *Pattern classification*. A Wiley-Interscience Publication.

Kasi, A.B.U., Jing, J., Westover, M.B., et al., 2025. Continuous EEG in Day to Day Neurocritical Care – A Case Based Review. *Curr Treat Options Neurol*, 27, 29. https://doi.org/10.1007/s11940-025-00838-6

Kim, J.A., Zheng, W.-L., Elmer, J., et al., 2022. High epileptiform discharge burden predicts delayed cerebral ischemia after subarachnoid hemorrhage. *Clin Neurophysiol.*, 141(1), 139-146. doi:10.1016/j.clinph.2021.01.022.

Kondziella, D., Friberg, C..K., Wellwood, I., Reiffurth, C., Fabricius, M., Dreier J.P., 2015. Continuous EEG monitoring in aneurysmal subarachnoid hemorrhage: a systematic review. *Neurocrit Care*., 22, 450–461.

Lucas, B., Kanade, T., 1981. An iterative image registration technique with an application to stereo vision. *In: Proceedings of Imaging Understanding Workshop*, 121-130.

Meila, M., 2007. Comparing clusterings – an information based distance. *J. of Multivariate Analysis.* 98, 873-895.

Murashov, D., Obukhov, Y., Kershner, I., Sinkin, M., 2023. An Algorithm for Automated Detection of Delayed Brain Ischemia Indicator from Video-EEG Monitoring Data. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, XLVIII-2/W3-2023, 187–192. https://doi.org/10.5194/isprs-archives-XLVIII-2-W3-2023-187-2023, 2023.

Murashov, D., Obukhov, Y., Kershner, I., Sinkin, M., 2023a. An Algorithm for Detecting Artifacts in Video Recordings of Long-Term Video-EEG Monitoring Data for the Diagnostics of Delayed Cerebral Ischemia, *2023 IX International Conference on Information Technology and Nanotechnology (ITNT)*, Samara, Russian Federation, 1-5, doi: 10.1109/ITNT57377.2023.10139085.

Obukhov, Y., Kershner, I., Sokolov, A., Okuneva, I., Sinkin, M., 2024. Monitoring of the Dynamics of Sporadic Epileptiform Discharges of Electroencephalograms in Delayed Cerebral Ischemia After Subarachnoid Hemorrhage, *2024 26th International Conference on Digital Signal Processing and its Applications (DSPA)*, Moscow, Russian Federation, 1-4. doi: 10.1109/DSPA60853.2024.10510099.

Rosenthal, E.,S., Biswal, S., Zafar, S.,F., et al., 2018. Continuous electroencephalography predicts delayed cerebral ischemia after subarachnoid hemorrhage: A prospective study of diagnostic accuracy. *Annals of Neurology*, 83(5), 97-106. https://doi.org/10.1002/ana.25232

Santana, L.S, Diniz, J.B.C, Rabelo, N.N., Teixeira, M.J., Figueiredo, E.G., Telles, J.P.M., 2024. Machine Learning Algorithms to Predict Delayed Cerebral Ischemia After Subarachnoid Hemorrhage: A Systematic Review and Meta-analysis. *Neurocrit Care*, 40(3), 1171-1181. doi: 10.1007/s12028-023-01832-z.

Trinh D.-H., Daul C., 2019. On Illumination-Invariant Variational Optical Flow for Weakly Textured Scenes. *Computer Vision and Image Understanding*. 179, 1-18. https://doi.org/10.1016/j.cviu.2018.11.004.

Zheng, W.-L., Kim, J.A., Elmer, J., et al., 2022. Automated EEG-based prediction of delayed cerebral ischemia after subarachnoid hemorrhage, *Clin Neurophysiol.*, 143, 97-106, https://doi.org/10.1016/j.clinph.2022.08.023.