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APPLIED RESEARCH

Two-Stage Approach With Combination of Outlier Detection Method and Deep Learning Enhances Automatic Epileptic Seizure Detection

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ABSTRACT Many approaches to automated epileptic seizure detection share a common challenge — the trade-off between recall and precision. This study aims to develop a novel approach for reducing false positive predictions in seizure detection tasks applied to real-world EEG recordings. We propose a multi-stage modeling framework, for which the novelty lies in combination of traditional machine learning outlier detection with state-of-the-art convolutional neural networks. Our dataset includes raw epileptic EEG data directly from the hospital. Continuous wavelet analysis is employed for EEG preprocessing and feature extraction. We evaluated the performance of the proposed two-stage algorithm, and it demonstrated a slight decrease in recall but a significant improvement in precision in comparison to machine-learning-only or neural-network-only algorithms. We hypothesize that this finding aligns well with our previous research and relates to the fundamental properties of epileptic EEG, including the extreme behavior of seizures. Finally, we propose a potential practical application of the developed approach within a clinical decision support system.

INDEX TERMS Clinical decision support system, continuous wavelet transform, convolutional neural network, EEG, epileptic seizure detection, multi-stage approach, one-class support vector machine.

I. INTRODUCTION

Epilepsy is a chronic neurological disorder characterized by rare recurring seizures triggered by abnormal brain activity [1]. These seizures can involve various symptoms such as loss of consciousness, uncontrolled movements, and other manifestations that significantly impact a person's quality of life [2]. According to the World Health Organization, there are over fifty million people worldwide affected by epilepsy [3]. Therefore, development of effective antiepileptic treatment is a paramount objective. Medicine and neuroscience have made significant strides in this field, with up to 70% of patients achieving remission with appropriate medications. For cases resistant to drugs, surgical interventions and neurostimulation are viable options [4], [5], [6], [7]. However, successful treatment begins with accurate diagnostics. Consequently, there is a pressing need for precise and practical methods for diagnosing epilepsy.

In contemporary medical practice, electroencephalography (EEG) — a non-invasive method for measuring the brain's electrical activity [8] — stands as the primary clinical diagnostic tool for epilepsy. Diagnosis entails continuous patient

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monitoring, interpretation of EEG signals, and identification of specific epilepsy-related patterns, notably spike-wave discharges (SWDs) [9]. The prevailing approach to EEG analysis involves visual inspection and manual interpretation, offering relatively precise diagnosis but presenting numerous challenges for epileptologists. Epileptic seizures are rare occurrences, necessitating a representative number of events for analysis, often requiring prolonged EEG monitoring. Compounding this challenge is the highly variable nature of epileptic seizures, ranging from brief and inconspicuous episodes to prolonged periods of intense abnormal activity [10]. Consequently, analyzing extensive EEG datasets using conventional methods can be time-consuming and arduous. Hence, there is a pressing need for automated tools in epilepsy diagnostics, such as Clinical Decision Support Systems (CDSS) [11], capable of detecting suspicious "seizure-like" episodes [12]. The development of CDSS represents a significant scientific endeavor, offering the potential to expedite the screening process and provide alternative diagnostic insights [13].

To date, extensive research has been conducted in the field of EEG-based automated seizure detection. Some studies focus on rule-based expert systems [14], while others employ statistical models for seizure identification [15]. Another promising approach is machine learning (ML). Recently, there has been a notable increase in studies successfully implementing various ML algorithms for epilepsy diagnostics [16], [17], [18], [19]. Recent systematic review on ML algorithms for epilepsy detection [19] addresses and questions some trends in this field. There are papers that report some outstanding results with up to 100% *recall* [20], [21]. All developed ML models aim to provide intelligent systems to assist the neurophysiologists' task, and intelligence suggests learning, so the data on which these potential systems are trained becomes crucial. According to the review, the most popular databases, like the ones from the University of Bonn or the Children's Hospital of Boston – Massachusetts Institute of Technology, can be extremely limited, include different types of recordings as well as patients with various conditions. Usage of such data may mislead the classification results. ML models applied in all aspects of medicine should be aligned with the medical problem their dealing with and not just focus on model with the highest classification results that possibly have no actual impact on the medical problem. In our study we addressed this issue by considering raw EEG dataset, collected through routine clinical practice.

In recent years, the field of deep learning (DL) has also witnessed significant advancements, with artificial neural networks (ANNs) demonstrating superior performance in solving various problems using data from diverse modalities, such as images, texts, and audio signals. Consequently, numerous researchers have explored the application of ANNs in the context of epileptic seizure detection [22], [23], [24]. For ANNs, EEG wavelet spectra exhibit a structure similar to images, which allows the task of seizure detection to be partially substituted with the task of image classification [25], [26], [27], [28]. In this formulation, ANNs have maintained leading positions in various benchmarks such as ImageNet [29] since the introduction of AlexNet in 2012 [30]. The standard choice for this type of task is the convolutional neural network (CNN).

DL offers certain advantages over ML. For instance, when the task is reduced to an optimization problem, CNNs can achieve better results and do not require a significant amount of work on manual feature engineering. However, careful feature engineering based on expert domain knowledge of data can lead to higher interpretability in ML, which is crucial for medical AI applications [31], [32], [33].

Although some of the proposed methods hold promise for real-world medical applications, there is undoubtedly room for improvement. A common challenge for many methodologies has been low precision. Hence, the primary objective of this study was to devise a strategy for mitigating the occurrence of false positives (FP). As a base we used achievements of our previous research — for more details see section "Related work".

Pipeline of our study is illustrated in Fig. 1. In the first preliminary phase, we perform a raw clinical EEG data preprocessing, which included basic filtration and artifact removal. Next, we consider the representation of the signal in the time-frequency domain using the continuous wavelet transform. All details can be found in the section "Materials and methods".

In the second step of the study, we considered and compared two one-step approaches for seizure detection. The first method utilized our earlier work, employing one-class support vector machine (OCSVM) to identify outliers in the EEG signals, drawing inspiration from extreme value theory. The second method leveraged DL, specifically a CNN for image classification. A comparison of two algorithms based on outlier detecting OCSVM and on CNN showed that both methods exhibited some difference in recall but not in precision, and precision was generally low ($\sim 12\%$).

The high number of FPs produced by both the OCSVM and CNN methods can be attributed to the well-known data imbalance in epileptic datasets. With this in mind, we considered a potential improvement to our method: the implementation of multi-stage algorithms, which incrementally enhance the quality of predictions using information from previous stages. In classical ML, multi-stage algorithms have been successfully implemented to solve a wide range of problems and are considered the de facto standard in the IT industry [34], [35]. Multi-stage models are also employed in DL, for example, in computer vision tasks such as segmentation [36] and alpha matting [37]. While multi-stage solutions exist in the seizure detection field [15], the prospect of combining ML and DL in a single algorithm remains a relevant question.

Consequently, in the third phase of our study, we proposed a novel two-stage "OCSVM + CNN" algorithm to automatic seizure detection. In the first stage, we aimed to filter out

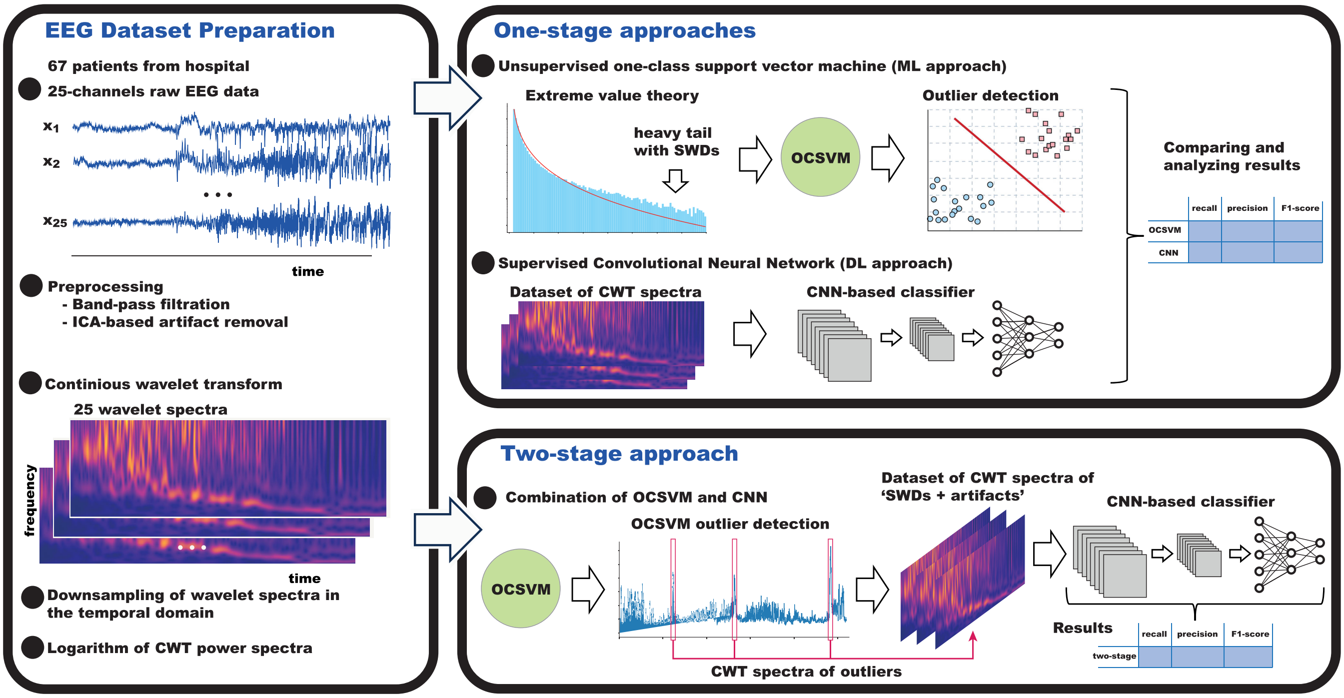

FIGURE 1. General pipeline of the study. EEG data from an epilepsy clinical dataset were preprocessed and used to compare two distinct approaches for seizure detection: (i) one-stage and (ii) two-stage approaches. Subplots here show examples of raw EEG data and calculated wavelet spectra as well as preprocessing pipeline. For the one-stage approach, we considered two potential methods. The first method employs a one-class classifier (OCSVM) to identify outliers in the EEG signals, drawing inspiration from extreme value theory. Two subplots here schematically show the basic principle of outlier detection and extreme value basis – heavy-tailed PDF with seizures as extreme events. The second method leverages deep learning, specifically a convolutional neural network (CNN) for image classification, which uses logarithmic wavelet spectra as input. One of subplots here schematically illustrates basic architecture of CNN. The results of this comparison, combined with the well-established concept of multi-stage approaches in classification, motivated the proposal of a novel two-stage algorithm based on the combination of OCSVM and CNN. The two-stage algorithm was evaluated on the same EEG epileptic dataset and demonstrated a slight reduction in recall but a significant improvement in precision compared to the one-stage approaches. Subplots here illustrate the results of OCSVM as outliers in averaged wavelet energy and corresponding wavelet spectra that are fed to CNN.

the majority of normal activity using a relatively simple and interpretable OCSVM. Subsequently, in the second stage, we employed a more complex model based on CNN to differentiate between the remaining FPs and true seizures present in the data. We evaluated the performance of this two-stage algorithm and compared it to the two initial one-stage algorithms. The results were promising: the two-stage "OCSVM + CNN" algorithm exhibited a marginal decrease in recall (82%) accompanied by a significant increase in precision (56%), which is a big step forward in comparison to all previous approaches.

II. RELATED WORK

Earlier we addressed the challenge of seizure detection using a ML approach. Our aim was to leverage insights from extensive research on epileptic EEG to develop an ML classifier within the context of CDSS. For instance, in our feature engineering process, we considered the known frequency characteristics of epileptic EEG [38]. Specifically, the primary rhythm of epileptic seizures is often confined to a characteristic frequency band, such as 1–5 Hz in human focal epilepsy. As a result, EEG activity within this band exhibits significant differences between epileptic and normal states, enabling us to effectively narrow down the feature space on the frequency scale.

Moreover, we applied our understanding of the temporal dynamics of epileptic seizures. In our previous research [39], we investigated the temporal dynamics of seizure-like patterns in mice following induced ischemic stroke, a condition known as post-stroke epilepsy. Specifically, we examined the wavelet energy of EEG signals across various frequency ranges, identified local maxima, and constructed probability density functions (PDFs) for these maxima within each frequency range. Our findings revealed that within a specific frequency range (22–24 Hz), the PDF exhibited an exceeding tail, indicative of extreme behavior, as suggested by extreme value theory [40], [41]. Consequently, we hypothesized that these induced seizures represent extreme events occurring within this particular spectral range. In our subsequent study [42], we validated this hypothesis using WAG/Rij rats with genetic predisposition to absence epilepsy, which naturally develop epileptic SWDs. Once again, we analyzed the wavelet energy of EEG signals across different frequency ranges and observed a "heavy-tailed" PDF within the frequency range of 5–9 Hz corresponding to SWDs in WAG/Rij rats, further supporting our interpretation of epileptic seizures as extreme events. Furthermore, our investigations extended to human subjects with focal epilepsy, where we observed a similar "heavy-tailed" PDF of wavelet energy but only within the spectral range associated with epileptic seizures in humans (1–5 Hz) [43]. This consistency across different forms of epilepsy suggests that extreme behavior is a common trait, albeit manifested within specific frequency ranges. Extreme events represent sudden abnormal deviations of a nonlinear dynamical system from its typical behavior [44] and are often regarded as anomalies or outliers in data. Therefore, we posit that these insights support the adoption of specialized techniques designed for outlier detection [45]. In our most recent studies [46], [47], we evaluated various supervised and unsupervised ML algorithms for outlier detection, employing different approaches to construct the feature space.

Interestingly, despite significant variations in the approaches tested, they yielded similar results. For instance, both the unsupervised OCSVM [45], [48] and the supervised RandomForest [47], [49] demonstrated comparable performance in terms of recall, achieving approximately 77.0% and 78.7%, respectively. Notably, in both cases, recall tended to exhibit one of two opposite values: either 100% or 0%, indicating the detection of all seizures or the absence of any seizure detection. Statistical analysis, as presented in [45], revealed that datasets with 100% recall exhibited distinct features of extreme behavior, characterized by pronounced heavy tails in their PDFs, whereas datasets with 0% recall lacked these features. This observation led to the hypothesis that the presence of extreme behavior is a crucial factor for the effective performance of the ML classifier in this context. Consequently, we concluded that the classification quality is relatively independent of the type and specific features of the classifier, suggesting that even a basic OCSVM can yield robust results. With the OCSVM, we achieved a recall of 77.0% and a precision of 12.7%. Based on these findings, we developed a CDSS aimed at reducing the manual workload associated with EEG interpretation. Specifically, the ML classifier can be utilized to identify suspicious EEG segments for subsequent human analysis. Despite the lower precision, the infrequency of epileptic seizures results in an acceptable number of FPs. Therefore, analyzing only the EEG segments predicted by the ML classifier, rather than the entire recording, leads to a significant (up to 95%) reduction in human expert workload [45].

Our earlier investigations have underscored the notion that simply fine-tuning algorithms and adjusting features may not substantially enhance the performance of the ML classifier. Addressing this issue demands fundamental changes to the approach itself. So we approached the problem from a different angle and considered an approach based on outlier detection, inspired by the theory of extreme events, only as the first step in creating a more effective algorithm. The second step is to utilize DL for classifying all events identified in the first step as epileptic and non-epileptic events. Thus, we arrive at a two-stage approach with a combination of outlier detection methods and DL that enhances automatic epileptic seizure detection.

TABLE 1. Characteristics of the dataset used in the current study.

Characteristic	min	mean	max
Seizure duration (seconds)	47	109.9	250
Seizure number per patient	1	1.8	5
Record duration (hours)	1.8	12.2	84.2
Interval between seizures (hours)	0.1	4.5	59.2

III. MATERIALS AND METHODS

A. EXPERIMENTAL DATASET

The dataset used in this study was collected at the National Medical and Surgical Center named after N.I. Pirogov of the Ministry of Health of the Russian Federation (Moscow, Russia). Dataset includes anonymized data of 83 subjects, who all were patients of the Center in 2017–2019. Medical procedures were carried out at the Center following the Helsinki Declaration and medical regulations of the Center, and were approved by the local ethics committee. All patients provided written informed consent before the treatment. The monitoring was conducted during normal daily activities, including sleep and wakefulness. All 83 patients were diagnosed with focal epilepsy, and epileptic foci were located in the frontal, temporal, or parietal regions of the left, right, or both hemispheres, thus there was no uniformity of the diagnosis. The duration of the recording varied from 8 to 84 hours, depending on the patient's condition and the number of recorded seizures. EEG data were examined and deciphered by experienced epileptologist, who marked all epileptic episodes. During the observation period, each patient had from one to five epileptic seizures. It is worth noting that the total duration of all recordings in our dataset was 816.4 hours, while seizure activity was in total only 3.6 hours (0.44% of the full length of records) or 117 seizures. While patients were periodically exposed to physiological trials (photic stimulation and hyperventilation) aimed to provoke epileptiform activity [50], [51], none of the seizures were caused by them, i.e. all seizures were spontaneous. The dataset's detailed numerical characteristics can be found in Table 1.

EEG signals were recorded with "Micromed" encephalograph (Micromed S.p.A., Italy) at sampling rate of 128 Hz with $N = 25$ EEG channels according to the international "10–20" scheme [52]. As we mentioned in Introduction, OCSVM predictions were poor for specific 16 patients in the previous study on the same dataset [45]. PDFs of wavelet energy for those patients were not "heavy-tailed" and did not demonstrate pronounced extreme behavior.

We attributed the observed performance limitations to the presence of numerous data outliers unrelated to epileptic activity. These outliers often originate from sources such as muscle activity or external influences on the EEG electrodes and wires. Eliminating such artifacts typically necessitates sophisticated preprocessing techniques requiring human expert intervention. As outlined in the Introduction, our primary objective is to develop a method with potential applications in clinical decision support systems (CDSS). The design of such a system necessitates minimal human involvement, ideally limited to the final diagnostic stage where expert judgment is paramount. Consequently, all preceding steps should be automated, restricting the range of applicable preprocessing techniques. Our previous research [45] demonstrated a correlation between classifier performance and data contamination by artifacts. The present study is constrained by the lack of suitable preprocessing techniques within the scope of our task to address the poor data quality.

As a result, we decided to exclude these 16 patients and keep the data of the rest 67 for this research.

B. DATA PREPROCESSING

In this paper, we evaluated several approaches to epileptic seizure detection, all of which utilized the same data preprocessing pipeline. Raw EEG signals are highly susceptible to physiological artifacts and external noise, which becomes even more pronounced in prolonged recordings [53]. Certain noise components, such as breathing and muscle artifacts, exhibit distinctly low or high frequencies. Consequently, we employed a band-pass filter (Butterworth 1–60 Hz) to mitigate their impact. Additionally, a 50 Hz notch filter was used to suppress power grid interference. Other artifacts, such as blinking, interfere with frequency range of EEG, so to remove them we used more advanced procedure based on independent component analysis (ICA) [54] with the help of *Fieldtrip* toolbox for MATLAB [55].

C. EEG SIGNALS REPRESENTATION IN TIME-FREQUENCY DOMAIN

EEG signals were analyzed and diagnosed using ML and DL algorithms in the time-frequency domain. For this purpose, we used continuous wavelet transform (CWT) of preprocessed EEG signals [56], [57]. For each of the EEG signals $x_n(t)$, CWT performs convolution with the set of basis functions $\psi_{s,\tau}$:

$$W_n(s,\tau) = \int_{-\infty}^{\infty} x_n(t)\psi^*_{s,\tau}(t)dt, \tag{1}$$

where $n = 1, 2, \ldots N$ is the number of EEG channel ($N = 25$), $W_n(s,\tau)$ are the coefficients of the wavelet transform, and $*$ denotes complex conjugation. Each basis function $\psi_{s,\tau}(t)$ is obtained from the same original function ψ_0, known as mother wavelet:

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi_0\left(\frac{t-\tau}{s}\right), \tag{2}$$

where s is the time scale defining expansion and compression of the mother wavelet and τ is the time shift of the mother wavelet. Here the complex Morlet wavelet was used as the mother wavelet:

$$\psi_0(\eta) = \frac{1}{\sqrt[4]{\pi}}e^{j\omega_0\eta}e^{-\frac{\eta^2}{2}}, \eta = \frac{t-\tau}{s}, \tag{3}$$

where $\omega_0 = 2\pi$ is the central frequency of the Morlet wavelet. For this value of ω_0 we have a simple relationship between wavelet transform scales and frequencies $f \approx 1/s$.

Then, we considered wavelet power (WP) as:

$$w_n(f,\tau) = |W_n(f,\tau)|^2, \tag{4}$$

We used WP for each EEG channel in the frequency range of 1–40 Hz as an input for the models. WP was chosen as it is one of the most common CWT-based characteristics for describing the time-frequency structure of EEG [56]. Frequency range 1–40 Hz is generally considered acceptable for studying both normal and pathological EEG activity as it includes all main rhythms of EEG: delta, theta, alpha, beta bands [58].

In our previous studies [13], [46], [47], we segmented WP into non-overlapping 60-second intervals and averaged WP-based features within each interval. The selection of the 60-second interval length was based on the average duration of seizures, which typically range from 60 s to 120 s [59]. This approach was aimed to decrease the complexity of the EEG data, effectively downsampling the data in the temporal domain. However, a notable issue with this method was that an interval could include a combination of seizure and normal EEG segments. While this did not significantly impact time-averaged WP-based features used in ML algorithms, it posed challenges for CNN applications.

For CNN, the task of seizure detection is akin to image classification, where entire seizure and partial seizure intervals could be considered distinct classes, potentially leading to classification errors. To address this issue, we re-evaluated our approach to segmenting EEG signals and proposed the use of 10-second intervals specifically for CNN analysis. This decision was based on the typical duration and frequency range of epileptic seizures. While shorter intervals could reduce the occurrence of mixed epileptic and non-epileptic activity, making intervals even shorter (e.g., 1–2 s) was not feasible. Epileptic seizures exhibit certain similarities with other EEG oscillatory patterns in terms of frequency range or specific waveforms, but they are among the longer EEG patterns, guided by nuanced temporal dynamics. CNN processes independent segments, treating consecutive segments as separate entities rather than a continuous pattern, thereby overlooking temporal dynamics. Shorter segments of epileptic activity can be easily mistaken for non-epileptic patterns, thus a reliable seizure prediction with CNN necessitating analysis over extended intervals. Given that the epileptic frequency range is 1–5 Hz, a 10-second interval comprises 10–50 periods of epileptic activity, providing a sufficient basis for accurate prediction.

As we employed CNNs in our study, it is noteworthy that they generally converge more rapidly and stably when the input data conforms to a normal distribution with a mean close to zero and a constrained variance [60]. However, due to the fact that many values in the WP spectrum are close to zero, its overall power distribution is asymmetric and approximates an exponential distribution. To address this, we introduced a normalized logarithm of the WP as the input for the CNN:

$$w_n^{\log}(f,\tau) = \ln(w_n(f,\tau)), \tag{5}$$

$$w_n^{\mathrm{norm}}(f,\tau) = \frac{w_n^{\log}(f,\tau) - \mu(w_n^{\log})}{\sigma(w_n^{\log})}, \tag{6}$$

where $\mu(\cdot)$ is the mean value, and $\sigma(\cdot)$ is the standard deviation.

D. SOLVING THE PROBLEM OF CLASS IMBALANCE

As mentioned earlier, epileptic seizures are infrequent events that typically occur every few hours or even days during extended monitoring sessions. This naturally results in highly imbalanced epileptic datasets. Specifically, the total duration of all recordings in the present dataset exceeds 800 hours, of which over 99.5% corresponds to non-epileptic activity. Such pronounced data imbalance poses a significant challenge and is a subject of active research [61], [62], [63]. Training on imbalanced datasets often leads to poor generalization because the model tends to converge to a trivial solution that predicts a negative class (normal EEG in our case) for all samples.

To address this issue, we employed simple yet effective techniques: oversampling of the minority class (seizures) and undersampling of the majority class (non-seizures) [64]. Specifically, oversampling involves increasing the likelihood of epileptic segments being selected for training, while undersampling reduces the likelihood of non-seizures segments being included in the training set.

In a signal comprising L segments, the probability of each segment being selected for training is uniform. However, when oversampling/undersampling is applied to an imbalanced dataset containing, the probability of selecting normal segments becomes F_n, while the probability for epileptic segments is F_e:

$$L = L_e + L_n \tag{7}$$

$$F_e = \frac{1}{2L_e}, F_n = \frac{1}{2L_n}. \tag{8}$$

where L_n is the number of segments with normal activity and L_e is the number of segments with epileptic activity.

Furthermore, to enhance the robustness of the model during training, we employed augmentation techniques. Data augmentation involves artificially increasing the size of a dataset by making minor modifications to the original data. In this study, we utilized two augmentation approaches:

- random mirroring of EEG signal in time dimension;
- SpecAugment [65] which is applied directly to WP and involves zeroing of random frequency and/or time range.

E. ONE-STAGE OCSVM-BASED METHOD

In this study, we employed the OCSVM machine learning approach, based on the method proposed in [45]. We utilized a SVM with a Gaussian kernel and standardized predictors. Classifier optimization was performed using the Iterative Single Data Algorithm (ISDA) [66]. To train the OCSVM, we employed a variant of k-fold cross-validation. The dataset was randomly permuted and split up into k groups or folds. For each iteration, one group served as the test set, while the remaining $(k-1)$ groups formed the training set [67]. In our study, we used the data from a single subject as the dataset and chose the standard value of $k = 10$. The key parameter in OCSVM is the threshold, representing the estimated percentage of outliers in the data. In this instance, we set the OCSVM threshold to 0.25%.

For the OCSVM, the input was prepared in a similar manner to our previous studies [45]. The features for the OCSVM algorithm were extracted based on the domain knowledge of the time-frequency structure of epileptic EEG. Specifically, for the previously introduced 60-second intervals of EEG, the WP values were averaged over:

- 2–5 Hz frequency band of epileptic activity;
- 25 EEG channels;
- length of each time interval (60 s).

Mathematically it can be written as:

$$E(f,\tau) = \frac{1}{N}\sum_{i=1}^{N} W_n(f,\tau), \tag{9}$$

$$e = \frac{1}{\Delta T \Delta F} \int_{f_0}^{f_0+\Delta F} \int_{\tau_0}^{\tau_0+\Delta T} E(f,\tau) df d\tau, \tag{10}$$

where $f_0 = 2$ Hz is the lower bound of frequency band, $\Delta F = 3$ Hz is the width of of frequency band, $\Delta T = 60$ s is the length of time interval, and τ_0 is the starting time point of the interval. The averaged WP values e in Eq. (10) were used as input for OCSVM.

F. ONE-STAGE CNN-BASED METHOD

As DL approach in this study we have chosen CNN of the ResNet-18 architecture [68], as it stands as the conventional choice for image classification tasks.

This architecture comprises a combination of well-established components, including convolutional, average pooling, fully-connected, and batch normalization [69] layers. These layers are interconnected by ReLU non-linearities. A key distinguishing feature of this architecture is its incorporation of residual layers, which effectively address the problem of vanishing gradients [70] and promote a smoother loss landscape, facilitating the optimization process [71]. More formally, residual connections enable the network to learn residual mappings rather than the original mappings directly. This approach simplifies the learning process, as the model does not need to directly learn complex underlying mappings.

Despite the fact that this architecture is not the current state-of-the-art, it is a well-designed and thoroughly studied one that allows to avoid problems and bugs related to the design of a custom architecture. In our implementation,

CNN performs binary classification of 10-second intervals of EEG recording after CWT. Since the original architecture was designed to classify RGB images across multiple classes, we made two modifications to the architecture:

- The first convolutional layer is adjusted to accept 25 input channels. This change ensures that the CNN can process the 25-channel WP spectra correctly.
- The final fully-connected layer is modified to have a single neuron. This single neuron is used to output a binary prediction, that represents the confidence of the CNN that the processed segment contains epileptic activity.

To train the one-stage CNN model, we utilized 100 examples chosen for training each epoch, with approximately 50% containing epileptic activity. This was achieved through custom probabilities as detailed in Eqs. (8). The quantity of 100 examples was selected to ensure a reasonable training duration.

CNN training hyperparameters were as follows:

- number of epochs: 10,
- learning rate: 0.001,
- butch size: 4,
- optimizer: Adam.

Binary Cross Entropy (BCE) was used as a loss function for CNN:

$$\mathrm{BCE} = -\frac{1}{N_{data}} \sum_{i=1}^{N_{data}} (t_i \log(p_i) + (1 - t_i) \log(1 - p_i)), \quad (11)$$

where N_{data} is the number of training samples, p_i is the model predictions, t_i is the true labels.

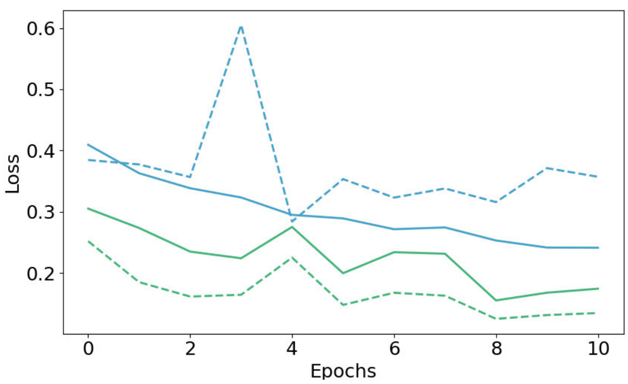

FIGURE 2. Learning curves for one-stage CNN (green lines) and for CNN from the two-stage approach (lines). Solid lines represent the loss function evaluated on the training set, while dashed lines depict the loss function evaluated on the validation set.

G. COMBINED TWO-STAGE "OCSVM + CNN"-BASED METHOD

The two-stage algorithm, as previously mentioned, consists of OCSVM in the first stage and CNN in the second stage. The features and performance parameters of the OCSVM-based and CNN-based algorithms have been described in Sections III-E and III-F, respectively.

The primary distinction lies in the methodology employed to construct the training dataset and select samples for it. In the case of the two-stage model, half of the examples were drawn from segments with confirmed seizures, while the remaining half were selected from segments where the OCSVM model made a false positive prediction. Therefore for two-stage approach Eqs. (7) and (8) take form:

$$L = L_e + L_{FP} + L_{TN}, \quad (12)$$

$$F_e = \frac{1}{2L_e}, \quad F_{FP} = \frac{1}{2L_{FP}}, \quad F_{FN} = 0. \quad (13)$$

where L_{FP} is the number of segments where OCSVM made a FP prediction and L_{TN} is the number of segments where OCSVM made a TN prediction.

The CNN employed in the second stage of the proposed approach was trained using the same procedure as the one-stage CNN. For both neural network models, learning curves were closely monitored to assess the degree of overfitting. To mitigate the risk of utilizing an overfitted model, a checkpoint with the lowest validation loss was selected, implementing an early stopping technique, a common practice in deep learning (DL) [72].

Fig. 2 presents the learning curves for both CNN models. The single-stage CNN (green lines) exhibits no signs of overfitting. Furthermore, its validation loss consistently remains lower than the training loss, reflecting the relative simplicity of the sampled examples. These examples have been pre-filtered by the one-class support vector machine (OCSVM) in the two-stage approach. In contrast, the CNN from the "OCSVM + CNN" approach (blue lines) demonstrates a slight degree of overfitting after the midpoint of training. Its validation curve consistently exceeds the training curve. This observation may be attributed to several factors. First, the complexity of the samples is significantly increased, rendering the learning task inherently more challenging. Second, the OCSVM stage effectively removes most normal activity, leading to a decrease in the variability of training samples. This is an unavoidable consequence of the OCSVM preprocessing step.

We present the workflow diagrams for both one-stage algorithms and the two-stage algorithm in Fig. 3. In this scheme, oval frames represent data at different processing stages, while rectangular frames indicate specific data processing steps. The entirety of Fig. 3 illustrates the two-stage algorithm, with its components, Fig. 3A and Fig. 3B, corresponding to the one-stage OCSVM and CNN algorithms, respectively. In the first stage, OCSVM performs pre-filtration by predicting whether the 60-second segments contain epileptic activity. In the second stage, the segments predicted by OCSVM are inputted into the CNN model to enhance the prediction accuracy on 10-second segments.

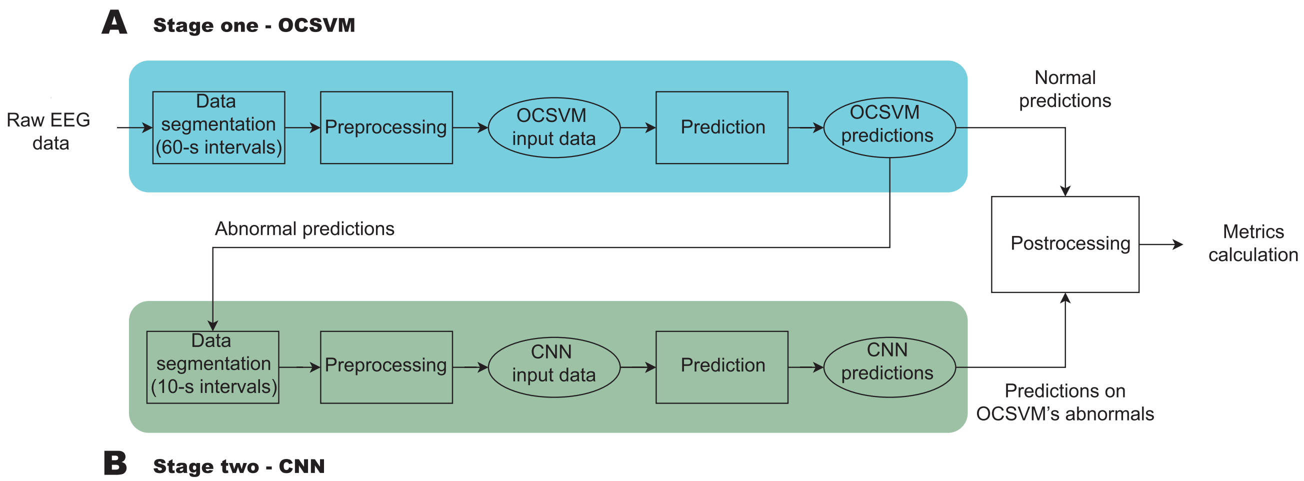

FIGURE 3. Unified pipeline illustrating the two-stage algorithm (entire figure) alongside the one-stage algorithms: OCSVM (A, top of workflow) and CNN (B, bottom of workflow). Oval frames represent data at various processing stages, while rectangular frames indicate the specific procedures executed on the data.

H. POSTPROCESSING

Upon analyzing the predictions of the one-stage CNN, we observed a large number of short duration predictions (10–50 s), as evident from the distribution of durations in Fig. 4 (green histogram). These short predicted segments lack neurophysiological significance. To further support this observation, we examined the distribution of seizure durations (blue histogram in Fig. 4) considering all seizures across all patients. As depicted in Figure 4, the minimum seizure duration exceeds 40 s, with the average seizure lasting over 100 s. This analysis leads us to infer that the short predicted intervals, particularly isolated ones, are likely false positives. In an effort to diminish the occurrence of FPs, we implemented post-processing on the model predictions. Specifically, we applied a median filter with a kernel size of $K = 7$ to smooth the output of the CNN. This filtering technique helps to reduce the stochastic nature of predictions, leading to the elimination of sporadic short FP predictions.

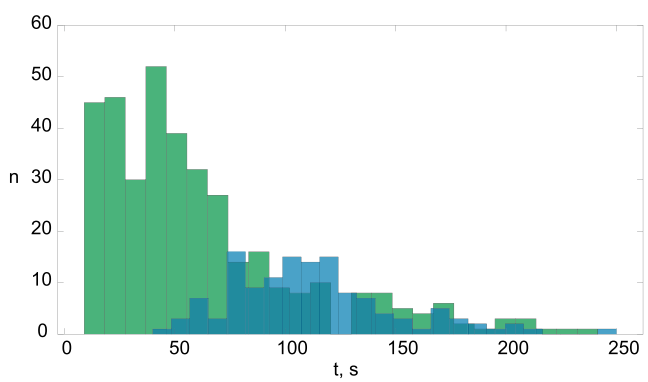

FIGURE 4. Distributions of durations for true epileptic seizures (blue) and prediction made by CNN (green).

It is a common practice for a binary classifier to generate predictions individually for each time segment. However, this standardized approach does not account for the nuanced characteristics of our task. As previously mentioned, seizures, even those of shorter duration, do not manifest as solitary 10-second segments. Analysis of the outcomes reveals that predictions often cluster into sequences of consistent class predictions — seizure or non-seizure — which aligns with the natural patterns observed in EEG data. In the context of CDSS, the primary focus is on identifying all epileptic seizures rather than pinpointing every 10-second segment with epileptic activity. The latter task is notably more intricate, as precise seizure detection entails identifying the onset and offset of each episode, a challenging feat even for seasoned epileptologists. Conversely, uncovering a "suspicious" segment containing seizure(s) suffices for CDSS, as its predictions are intended for human review and final decision-making.

In our study, we introduced an algorithm that transforms clusters of 10-second predictions into segments of varying lengths. The algorithm, illustrated in Fig. 5, is applied to the initial predictions (the first set of 33 segments in Fig. 5) and comprises two steps. Firstly, a naive merging is applied — neighboring segments of the same predicted class are merged together into a single longer segment of this class. The result of this step is shown as the second set of 7 segments. Secondly, an advanced merging process consolidates positive prediction segments that are separated by a single negative prediction segment into a unified longer positive prediction segment. The result of this step is shown as the third set of 6 segments. The second step may seem trivial, but it is rooted in a data-driven rationale: epileptic seizures do not abruptly cease, only to resume 10 seconds later. Therefore, we assume that such instances represent classifier inaccuracies, and the advanced merging step aims to correct these discrepancies.

I. EVALUATION

To evaluate the quality of the model, we used standard metrics for the classification task based on errors of the 1st and

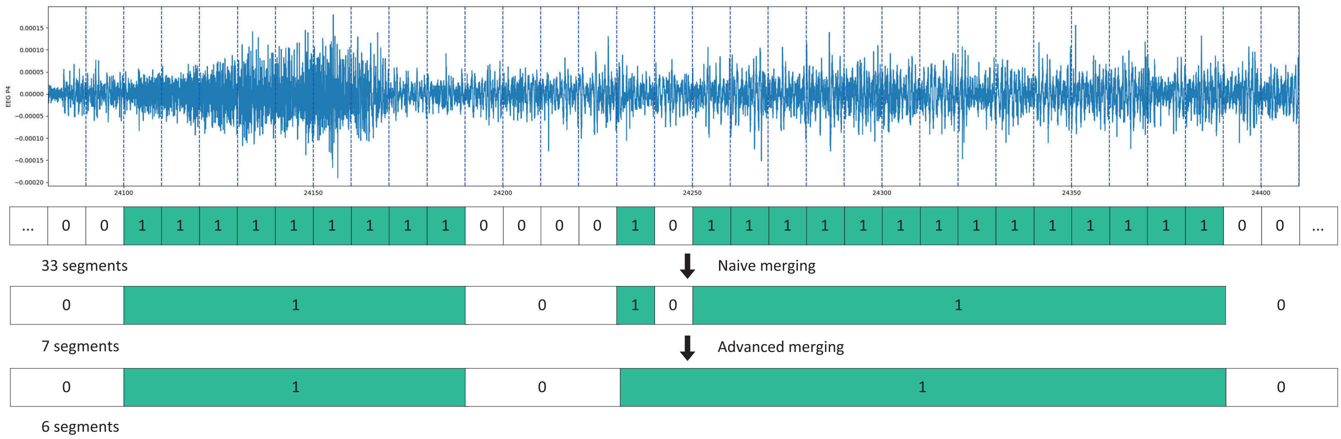

FIGURE 5. The initial predictions and proposed merging algorithm with two steps: naive merging of neighboring segments with the same predicted class and advanced merging of segments with positive prediction separated by one segment of negative prediction. EEG signal from channel P4 is depicted for clearer representation of examples.

2nd type from statistical hypothesis testing, namely *recall* (R), *precision* (P), and $F1$-*score* (F_1):

$$R = \frac{TP}{TP+FN}, \quad P = \frac{TP}{TP+FP}, \quad F_1 = \frac{2PR}{P+R}, \tag{14}$$

where TP, FP, and FN are the numbers of true positive, false positive, and false negative predictions, respectively.

Since we have multiple patients with individual numbers of TP, FP, and FN, we need to consider calculating metrics R, P, F_1 for the whole dataset. There are two common options for this:

- calculate metrics independently for each patient and then average them across all patients;
- calculate the total numbers of TP, FP, FN in dataset and then use them to calculate metrics.

The first option has an issue with *recall* metric. In our case, number of TPs is low, frequently only one seizure per patient, so missing this only seizure results in $R = 0$, which, in its turn, drastically affects averaged *recall*. The second option has a similar problem with *precision*: unusually high number of FP from few patients can decrease resulting *precision*. However, in our dataset, numbers of FPs are more or less consistent across the patients, so we chose the second option. Thus, in Eqs. (14) we used total numbers of TP, FP, and FN collected from all patients in dataset.

In a similar vein to postprocessing, the evaluation process must consider the intricacies of the task, necessitating the adaptation of criteria for defining TP, FP, and FN predictions. We have formulated a set of guidelines outlining how these metrics are calculated using segments of varying lengths, as demonstrated in Fig. 6. These guidelines are detailed as follows:

- If one or more predicted segments are within or intersect a T-second range of a true seizure segment, we designate them collectively as a single TP prediction (refer to Fig. 6A);
- Segments that do not intersect a T-second range of a true seizure are categorized as FP predictions (refer to Fig. 6B);
- In scenarios, where there are no predicted segments within a T-second range of a true seizure segment, we classify this as a FN prediction (refer to Fig. 6C).

The introduction of a T-second range acknowledges the inherent challenge in precisely defining the onset and offset of a seizure event. Additionally, it accommodates the possibility of underlying EEG activity preceding the onset, which may go unnoticed by human observers but still influences the neural network's performance [73]. Incorporating a T-second range is pertinent for a CDSS, focusing on identifying EEG segments with potential seizures. Here, we set $T = 60$ s based on the typical seizure duration.

It is crucial to highlight that before metrics can be computed, raw predictions must be translated into binary predictions. Hence, it is imperative to select a threshold to classify a 10-second segment into either a positive or negative class. To achieve this, we determined a threshold that optimizes *precision* while maintaining a high enough *recall* (greater than 0.8 in this study) on a validation set. This methodology aligns with the objectives of a CDSS, where the primary aim is to effectively detect the majority of seizures for a patient.

Traditional metrics such as R, P, and F_1, while suitable for binary classifiers, may lack representativeness when assessing results in the context of a CDSS, particularly when comparing outcomes among recordings of varying lengths. Epileptic seizures are not uniformly distributed throughout EEG signals, leading to potential inaccuracies in R and P values when shorter recordings contain more seizures or longer recordings have fewer seizures. In clinical practice, the recording duration between two patients can vary significantly, sometimes by an order of magnitude. Therefore, it may be more meaningful to focus on the absolute values of TP, FP, and FN or their hourly normalized equivalents—TP_h, FP_h, and FN_h:

$$TP_h = \frac{TP}{H}, \quad FP_h = \frac{FP}{H}, \quad FN_h = \frac{FN}{H}, \tag{15}$$

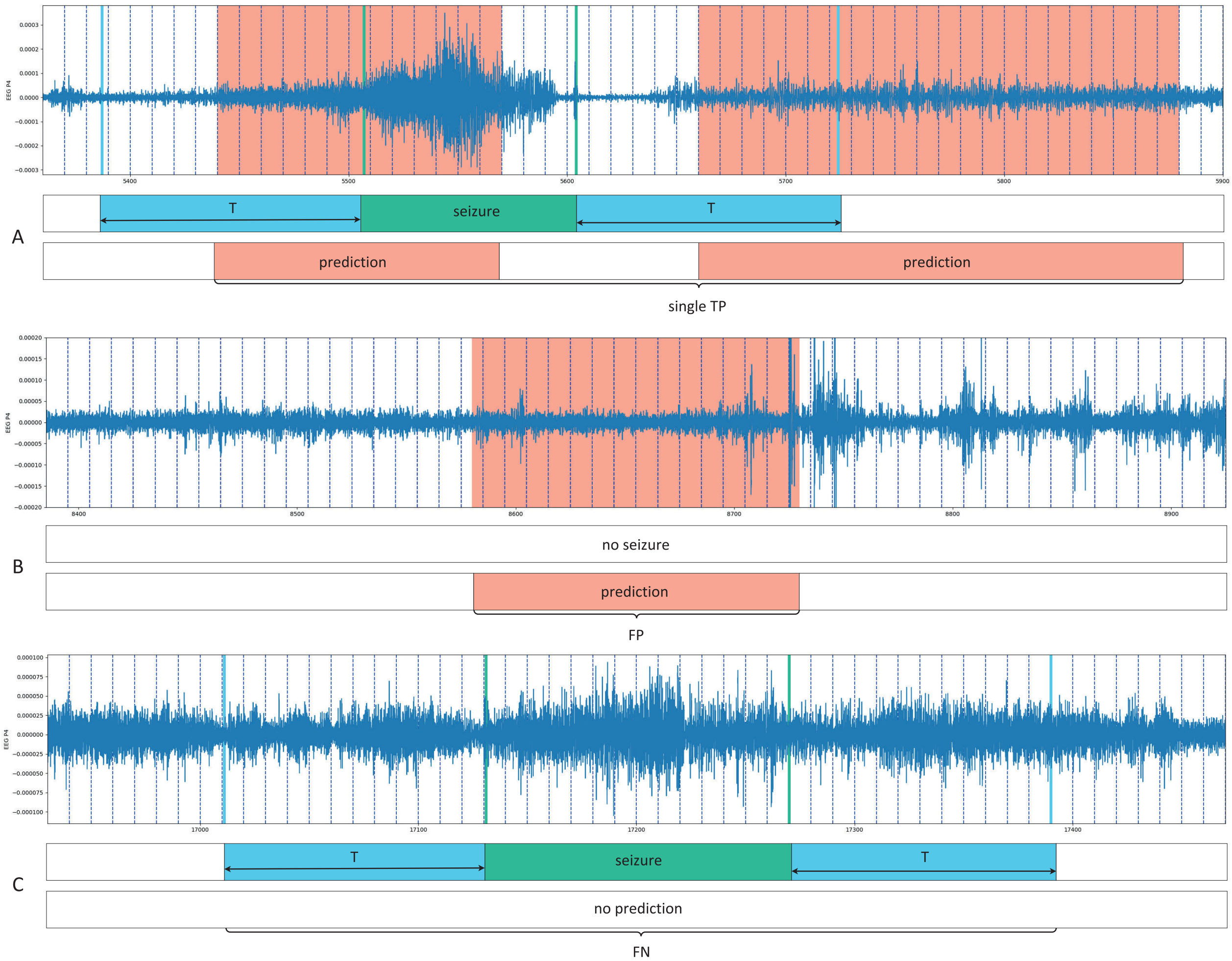

FIGURE 6. Examples illustrating rules for counting TP, FP, FN. Green corresponds to true seizures, blue – to T-second range of a true seizure, peach – to predictions. EEG signal from channel P4 is depicted for clearer representation of examples. (A) multiple predicted segments in T-second range of a true seizure are counted as single TP; (B) predicted segment outside T-second range of a true seizure is counted as FP; (C) seizure without any predictions in its T-second range is counted as FN.

where H is the total duration of current patient's EEG recording in hours.

IV. RESULTS AND DISCUSSION

In the Results section, we compare the performance of all three considered approaches: the one-stage OCSVM, the one-stage CNN, and the two-stage "OCSVM + CNN". The corresponding metrics are presented in Table 2. It is evident that the one-stage OCSVM and CNN models exhibit relatively similar performance: slight variations can be observed in *recall* (0.90 vs. 0.96) but not in *precision* (0.12 vs. 0.13). However, the combined *recall* and *precision* values result in a low $F1$-score of 0.21 and 0.23, respectively. These results are unexpected, as we anticipated the CNN, being a more intricate model, to deliver enhanced performance, particularly in terms of *precision*.

When considering the absolute metrics, FP_h stands out as the most notable. TP_h and FN_h act more as dataset descriptors in this context. Given that any effective CDSS necessitates high *recall*, TP_h and FN_h values should remain relatively stable across different methods. Conversely, FP_h directly signifies the CDSS's efficacy — the lower the FP_h, the fewer segments of EEG data require human scrutiny. The TP_h and FP_h values obtained for the CNN and OCSVM methods ($\mathrm{TP}_h = 0.12$, $\mathrm{FP}_h = 0.83$ and $\mathrm{TP}_h = 0.11$, $\mathrm{FP}_h = 0.85$, respectively) imply that a CDSS based on either approach would likely yield approximately one TP and 8-9 FP predictions for a standard 10-hour EEG recording. While manageable for individual cases, working with such a system could swiftly become taxing with an expanding dataset size.

Both the CNN and OCSVM approaches exhibit low *precision*, which, as previously mentioned, can be attributed to the inherent data imbalance in epileptic datasets. Seizures, being rare events (less than 0.5% of the dataset), display characteristics of extreme behavior. However, the significant number of false positives contradicts this notion. Our hypothesis posits that the extreme dynamics of seizures might be obscured by other outliers in the EEG, such as physiological artifacts. This creates an intriguing scenario: while seizures are infrequent, they are diluted by artifacts or noise at a ratio of 1 : 7 (as indicated by the *precision* values

TABLE 2. Performance metrics for all considered approaches to seizure detection.

Model	*precision*	*recall*	$F1$-score	FN	FP	TP	FN_h	FP_h	TP_h
OCSVM	0.1176	0.9020	0.2081	5	345	46	0.0123	0.8514	0.1135
CNN	0.1273	0.9608	0.2248	2	336	49	0.0049	0.8292	0.1209
OCSVM + CNN	0.5733	0.8431	0.6825	8	32	43	0.0197	0.0790	0.1061

obtained), and collectively, these events are still perceived as outliers in the EEG data.

The described temporal dynamics provide a foundation for most classifiers to deliver modest results. However, effectively distinguishing genuine seizures from artifacts necessitates the consideration of subtle EEG features. Our findings indicate that even advanced techniques like CNN face challenges in this regard. We believe that two key factors are at play: the aforementioned data imbalance and the variability of seizures. The variability of epileptic seizures introduces significant variance to the target class, which already has limited instances. In our scenario, this variance stems from differences in patients' conditions, particularly in terms of epilepsy focus localization and severity (refer to the Section III-A).

The combination of data imbalance and variability yields detrimental outcomes: ill-defined seizure features are magnified by a substantial volume of non-target examples, resulting in the previously observed low *precision*. While addressing variability is challenging due to its intrinsic nature in real clinical data, more sophisticated methods like CNN, capable of fine-tuning multiple features, stand a better chance of success. On the other hand, data imbalance can be more effectively mitigated using outlier-detecting techniques such as OCSVM, designed explicitly for handling imbalanced datasets. This rationale underscores the importance of employing the proposed two-stage approach.

Table 2 shows that the two-stage approach has a somewhat decreased *recall* ($R = 0.84$) but a massively increased *precision* ($P = 0.57$). This leads to a noticeable increase in $F1$-score ($F = 0.68$). These results are desirable, as our main goal was to find a way to increase the *precision* of CDSS. The two-stage approach has the lowest *recall* among the considered algorithms for seizure detection but this was expected. The first stage is data treatment with OCSVM, and this algorithm has the second lowest *recall*. The second stage works with predictions of OCSVM, so its *recall* cannot exceed that of OCSVM.

The absolute value metrics also demonstrate improvement. While TP_h and FN_h are virtually the same as for one-stage OCSVM, FP_h is ten times less than for either of the one-stage algorithms (0.08). This means that a typical epileptic EEG recording (about one seizure per 10 hours) may not suffer a single FP. Such performance makes this version of CDSS acceptable even for larger datasets.

The increased *precision* of the two-stage algorithm is a desirable but curious result. The fact that OCSVM and CNN provide lower *precision* separately, but increase it in combination, may indicate that these two methods appeal to fundamentally different features of EEG data. In fact, we know for a fact that OCSVM targets extreme behavior in EEG signals, so it confuses seizures with other outliers. Details of CNN's work are not so transparent but we can theorize based on the obtained results. In the second stage of the proposed algorithm, CNN aims to separate true seizures from artifacts, probably based on some fine EEG features, as we discussed earlier. However, in the one-stage algorithm, CNN wasn't able to do this reliably. It seems that the features used by CNN are not common between seizures and artifacts, but rather between seizures and some other activity on the EEG (''hinderance''). In this way, the CNN struggles to train properly on the initial dataset, probably due to its imbalance, but becomes much more reliable at separating seizures from artifacts after the ''hinderance'' is removed. In this context, the first stage performs a pre-filtering using OCSVM to reduce the data imbalance and facilitate further CNN-based classification. We believe that this is an interesting result from a fundamental point of view, as it inspires the implementation and combination of classification techniques from different fields.

V. LIMITATIONS AND FUTURE RESEARCH

This work has certain limitations and room for further research.

Firstly, algorithms used in our two-staged approach are not optimized. As a ML model we used OCSVM, which is widely considered to be a basic model. ML model can easily be substituted with another outlier detecting algorithm, so we are planning to test different approaches, which also would be an extension of our earlier study [46]. While we used initially strong CNN architecture (ResNet), we didn't conduct much research selecting the best possible CNN architecture for the task. Moreover, there are certain techniques for CNN improvement like generation of synthetic data [74], [75], thus, this can also become a goal for future study. Furthermore, the two-stage algorithm is not inherently limited to the combination of one-class support vector machine (OCSVM) and convolutional neural network (CNN). As previously stated, the fundamental principle of this approach is to first identify outliers in the EEG data and subsequently differentiate true seizures from false positives. Theoretically, any techniques capable of achieving these two objectives could be employed. Therefore, further research could explore various combinations of different techniques to identify the configuration that yields the most significant increase in precision for the two-stage algorithm.

One of the main limitation of the proposed two-stage approach is a lack of interpretability. This is the result of implementing CNN at the second stage. Lack of interpretability can become an issue if we strive to implement our CDSS in real clinical practice, where all methods should be highly transparent. The interpretability in the neural network based models is a subject of active research [76], so in our future work we will aim to implement some of the existing methods to increase the interpretability of the model. One way to increase the interpretability of CNN is to study important features, that CNN uses in classification, for example, via Grad-CAM approach [77]. In addition to making CNN's work more transparent, it can help compare the EEG features used by OCSVM and CNN, which may provide further insight into seizure detection.

Another important limitation of the proposed algorithm is calculation time. At the moment, the time to receive a prediction can be quite long — up to 10% of the duration of the recording itself. This is not critical when working with prerecorded data, but can become an issue during the possible transition to real-time. The bottleneck here is the computationally intensive CWT, so in our future research we plan to consider other similar techniques for time-frequency analysis, such as discrete wavelet transform, or narrower ranges in the time and frequency domains.

A further limitation stems from the previous point. While the use of 10-second time intervals as CNN inputs was theoretically justified, empirical support for this choice is lacking. Empirical validation, which would involve considering various time interval lengths and reiterating all data processing and CNN training steps to obtain classification results for each interval length, would be highly illustrative. However, the computationally intensive nature of the continuous wavelet transform (CWT) employed in this study hinders such an extensive exploration within a reasonable timeframe. Therefore, we propose exploring empirical validation with alternative, computationally less demanding EEG analysis methods, e.g. discrete wavelet transform [78] or empirical mode decomposition [79], as a future research direction.

For this study, we utilized an unstructured dataset directly acquired from a hospital setting to evaluate the proposed algorithm. While this dataset provided valuable insights, there is potential for further enhancement. Future research could benefit from employing larger and more diverse datasets to further validate the algorithm's capability for rigorous diagnostics.

It is important to note that any practical implementation of the proposed algorithm should be considered only after addressing the limitations discussed above. While optimizing the algorithm to enhance precision and reduce computational time can be achieved through straightforward testing of various techniques, other crucial aspects require more extensive investigation. These include increasing the interpretability and robustness of the method, which necessitates collaboration with specialized medical institutions to gain access to large datasets and expert consultation. Furthermore, any clinical decision support system based on this algorithm must be rigorously evaluated by clinicians using real-world data before its integration into clinical practice.

The primary objective of this research was to demonstrate the feasibility of a combined OCSVM and CNN two-stage classifier for epilepsy diagnostics. This paper presents the proposed algorithm and provides preliminary results. Therefore, while the limitations outlined in this section warrant further investigation, they do not detract from the scientific validity of our research.

VI. CONCLUSION

In this study, we investigated two distinct approaches for epileptic seizure detection: (i) machine learning based on OCSVM inspired by extreme value theory and (ii) deep learning based on convolutional neural network (CNN) for image classification. Both techniques were evaluated on an epileptic EEG dataset and the results were analyzed. We then used these results in conjunction with the established concept of multi-stage classification to propose a novel two-stage algorithm for seizure detection. The key feature and novelty of the proposed algorithm is the integration of an OCSVM, which performs data pre-filtering in the first stage, and a CNN, which improves prediction accuracy in the second stage. We compared the performance of the two-stage algorithm with that of the original algorithms and observed a marginal decrease in recall accompanied by a significant increase in precision.

We demonstrated that the proposed two-stage algorithm generates approximately ten times fewer false positive predictions than either of the two initial approaches. Consequently, we propose a possible practical application of this algorithm within a clinical decision support system suitable for analyzing even larger datasets.

Furthermore, we believe that the presented results hold significant implications. Detection of outliers is one of the fundamental tasks in medical data analysis. In many cases outliers are caused by artifacts and measurement errors and therefore lack any meaningful information. However, sometimes an abnormal value may be the result of inherent data variability and provide insight about the state of the system in study. The latter type of outliers can appear in the systems where high variability is natural, for example in the systems with extreme behavior. Extreme events in medical data can be quite diverse: from epileptic seizures studied in this paper [45] to cardiac crises measured through blood pressure data [80] and more exotic events found in temporal variability of brain signals [81] and third-moment statistics of the brain BOLD signals [82]. It is crucial to distinct between two types of outliers, and the situation is complicated by the fact that outliers of both types can coexist in the data of one patient. The proposed method aims to solve the task of separating noise-related outliers from system dynamics-related extreme events. Our findings also demonstrate the efficacy of a multi-stage algorithm, combining classification techniques from different domains, as a suitable tool for this task. We anticipate that these results will inspire further research in this area.

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