Childhood Epilepsy Syndrome Classification through a Deep Learning Network with Clinical History Integration

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***Abstract*—In this conference paper, we present TSA3-D, a novel two-stream 3-D attention module-based deep network aimed at classifying childhood epilepsy syndromes using multichannel EEG data. Unlike existing research primarily focusing on seizure detection, we emphasize syndrome classification, integrating clinical history such as age of onset, family history, and treatment responses as predictive features to enhance precision. We optimize EEG features through multichannel montage transforms to minimize artifact interference. TSA3-D incorporates channel-wise and dual spatial attention modules to improve feature learning. With data from 115 subjects covering seven epilepsy syndromes and a control group, our results demonstrate an outstanding accuracy of 99.52, surpassing existing state-of-the-art methods. This amalgamation of advanced deep learning and clinical history offers a promising avenue for precise syndrome classification, thereby facilitating improved diagnosis and tailored treatment strategies.**

I. INTRODUCTION

Epilepsy syndromes differ from single seizures in that they are typified by a collection of symptoms that usually appear simultaneously. Understanding these syndromes requires an understanding of the patient's clinical history, which frequently offers important insights into the patient's medical background, including the age of onset, seizure triggers, and other pertinent details. Worldwide, between 0.5% and 1% of children have epilepsy syndromes. These syndromes can significantly affect a child's cognitive development and emotional health, increasing their risk of mental retardation, emotional disorders, and inattentiveness. A variety of seizure types are commonly associated with epilepsy syndromes, such as infantile spasms (also known as WEST syndrome), febrile seizures plus (FS+), benign childhood epilepsy with centrotemporal spikes (BECT), childhood absence epilepsy (CAE), epileptic encephalopathy with continuous spike-and-wave during sleep (CSWS), and early infantile epileptic encephalopathy (EIEE). These syndromes are characterised by a distinct set of clinical features, symptoms, and EEG patterns. They also frequently show age-dependent traits, including prognosis, seizure triggers, and age of onset. Even though clinical history is crucial for diagnosing epilepsy syndromes, accurate identification and diagnosis are still difficult because of the lack of clinical experience and sophisticated analysis techniques. It is reported that at least 25% of epilepsy syndromes are misdiagnosed. For this reason, the creation of a reliable algorithm is crucial to the precise diagnosis and prognosis of paediatric epilepsy syndromes. EEG (scalp electroencephalogram) is a commonly used tool in epilepsy analysis. Since interictal EEG recordings are made during the times between seizures, they are especially significant because they show the most common condition of individuals with epilepsy. Interictal EEGs make up a sizable portion of the data in our recorded CHZU EEG database, which makes analysing them a useful method for diagnosing epilepsy syndrome. Promising outcomes in the analysis of epilepsy using interictal EEGs have been reported in earlier studies. For example, Bao et al. created a probabilistic neural network (PNN) that used interictal EEG features to detect epilepsy with high accuracy. In order to develop an automated and quick diagnosis system for adult epilepsy, Thomas et al. concentrated on spectral features and interictal epileptiform discharges (IEDs). In order to represent the sensor-level brain functional connectivity from interictal EEGs in generalised epilepsy, Cao et al. proposed a multivariate method. It is important to accurately classify childhood epilepsy syndromes because various syndromes may need different treatment

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modalities. Classifying childhood epilepsy syndromes based on interictal EEGs has received less attention than seizure detection, an area of research that has received considerable attention. An extensive study on the classification of typical childhood epilepsy syndromes using interictal EEGs is presented in this article. A two-stream attention module 3-D deep network (TSA3-D) is introduced for feature learning and fusion, utilising time-frequency and frequency-space EEG features, and is inspired by multistream deep networks.

II. Data Set Used

The CHZU epilepsy syndrome and normal control group EEG database are used. This includes information about the distributions of children's gender, average age, and recording duration. The EEG data were recorded from 115 children belonging to seven typical childhood epilepsy syndromes, including six well-known epilepsy syndromes: BECT, CAE, CSWS, EIEE, FS+, WEST, and one category labeled as "Else," along with a normal control group. Table I presents the clinical manifestations, onset age, background activity, and interictal EEG characteristics of the six known epilepsy syndromes. Notably, the onset age of EIEE and WEST is generally earlier than that of other syndromes, while the onset age span of the rest of the epilepsy syndromes is longer.

The raw EEGs were recorded using the international 10–20 system with 21 channels and a 1000-Hz sampling frequency by the NicoletOne-V32 video EEG instrument. Since the transient nature of epilepsy onset makes ictal EEGs difficult to capture, interictal EEGs typically account for 95% of the signal acquisition. Therefore, the analysis of interictal EEGs is more applicable for epilepsy syndrome classification. For each subject, most EEG data are within the interictal period. Given the high sampling frequency of 1000 Hz and to avoid generating an excessively large database, a 15-minute interictal EEG segment was randomly chosen for each subject. This random selection of EEG segments also helps assess the robustness of the proposed algorithm. The data labeling was performed with the assistance of neurologists at CHZU, and a segment splitting strategy was adopted based on the different recording durations of various subjects. For subjects with recording durations of less than 3 hours, interictal EEG segments without non-physiological artifacts were generally chosen. For those with recording durations longer than 3 hours, interictal EEG segments recorded during the sleep period were selected.

Preprocessing of the EEG data included the removal of 50-Hz power frequency interference, baseline drift correction, and bandpass filtering in the range of 0.5–70 Hz.

III. Signal Pre-processing

Electrical activity known as "biomedical signals" reveals important details about the physiological condition of the body. They are employed in medicine to track and diagnose illnesses. DWT, WPD, and other wavelet analysis techniques are useful instruments for processing, cleaning, and analysing biological

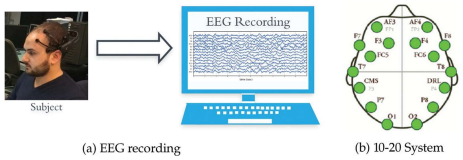

Fig. 1. EEG recording

signals. They can also be applied to feature extraction and artefact removal. This method can be used for a variety of biomedical signals, such as GSR, EEG, ECG, and EMG. The brain uses chemical and electrical impulses to process information. Brain activity is studied using a variety of methods, such as EEG, fMRI, and fNIRS. EEG is a portable and easily accessible method of directly measuring brain activity with great temporal resolution. fMRI is pricey and only useful for medical diagnosis, despite having a great spatial resolution.

A. Types of Brain Signals

- **Delta Waves (0.1-4 Hz)**
  Connected to slow wave sleep (SWS) and deep sleep, emotional processing, memory consolidation, and deep relaxation. Suppressed when conscious and may be more prevalent in neurological conditions like dementia and epilepsy.
- **Theta Waves (4-8 Hz)**
  connected to sleepiness, introspection, meditation, imagination, perception, and recollection. Suppressed when concentrating and solving problems, and may be more prevalent in mental health conditions including depression and anxiety.
- **Alpha Waves (8-12 Hz)**
  A sign of mental relaxation and closed eyes is linked to mental clarity, relaxation, and stress reduction and is suppressed when thinking, solving problems, and experiencing anxiety. May be more common with mental health conditions like ADHD.
- **Beta Waves (12-30 Hz)**
  Linked to focused attention, problem-solving, and active thinking, it is associated with attentiveness, concentration, and mental function and is suppressed when unwinding, meditating, and sleeping. May be more prevalent in mental illnesses like bipolar disorder and anxiety.
- **Gamma Waves (above 30 Hz)**
  plays a complex role in the brain's ability to perceive, process sensory information, and control movement. Connected to higher-order cognitive processes like memory, learning, and decision-making, suppressed under anesthesia and deep sleep, and potentially compromised in specific neurological conditions, including Parkinson's and Alzheimer's diseases.

Sure, here is the revised code:

B. Artifacts in EEG Signals

Electroencephalography (EEG) is a non-invasive technique used to record electrical activity in the brain. EEG signals can

be contaminated with various artifacts, which can distort the signal and make it difficult to interpret. Some of the most common types of artifacts include:

- **Motion artifacts:** These artifacts are caused by the physical movement of the person's body. They can produce sudden, high-value spikes in all channels of the EEG recording.
- **Muscular artifacts:** These artifacts are caused by any muscular contraction, such as grinding the teeth. They produce high-frequency bursts in the EEG recording.
- **Cardiac artifacts:** These artifacts are caused by the electrical activities of the heart. They appear as a weak form of the QRS wave of the heart and are most likely present in the temporal lobe channels, though they can sometimes be present in the frontal lobe channels.
- **Ocular artifacts:** These artifacts are slow, oscillating waves that appear on the frontal lobe, caused by eye movements or closed eyes.

C. Impact of Artifacts

EEG recordings can be distorted by artifacts, which can cause results to be interpreted incorrectly. They may also obstruct the ability to identify patterns of brain activity, which can complicate the analysis of EEG data. Artifacts may even result in a false positive in certain situations.

D. Artifact Removal

For the purpose of eliminating artifacts from EEG signals, numerous algorithms are available. But it is crucial to exercise caution when applying these algorithms because there is always a chance that some mental data may be lost in the process. Among the most popular techniques for removing artifacts are:

- **Bandpass filtering:** This method involves filtering the EEG signal to remove frequencies that are outside the range of normal brain activity.
- **Independent component analysis (ICA):** This method is a statistical technique that can be used to identify and remove artifacts from EEG signals.
- **Adaptive noise cancellation:** This method involves identifying a reference signal that is free of artifacts and using it to cancel out artifacts in the EEG signal.

IV. METHODOLOGY

A. Patient History

A patient's history is an essential part of the diagnosis of epilepsy and the classification of seizure types. The doctor needs to gather as much information as possible about what happened before, during, and after the seizure episodes. The patient may not be able to recall the details of the seizure, so eyewitness accounts from family members or friends are very helpful. The doctor may also ask about the patient's medical history, such as birth complications, head injuries, infections, medications, a family history of epilepsy or other neurological disorders, and any triggers or patterns of the seizures. The patient history can help the doctor rule out other causes of transient loss of consciousness, such as syncope, and identify the possible underlying etiology and syndrome of epilepsy. The patient's history can also guide the choice of further investigations, such as electroencephalography (EEG) and brain imaging.

Possible syncopal features: Ask about any symptoms or situations that may indicate a drop in blood pressure or reduced brain perfusion, such as sweating, lightheadedness, chest pain, palpitations, prolonged standing, or postural change.

Possible non-syncopal mimics: Ask about any signs or symptoms that may suggest an alternative diagnosis, such as fever, neck hyperextension, visual disturbance, headache, or limb weakness.

Abnormal brain activity: Ask about any abnormal sensations, movements, behaviors, or emotions that may indicate a focal seizure or an aura before a generalized seizure. The type and location of these symptoms may depend on the area of the brain affected.

Underlying aetiology: Ask about any features that may indicate the cause of the seizure, such as head injury, infection, drug use, or metabolic disturbance. The timing of these features in relation to the seizure is also important.

B. Differential Diagnosis of Seizures and Spells

When a patient presents with symptoms suggestive of a seizure, it is crucial to consider a broad differential diagnosis, as the event could be due to various causes beyond epilepsy. These include:

- Pre-syncope
- Transient ischemic attacks
- Migraine auras
- Paroxysmal movement disorders
- Sleep disorders
- Intracranial hypertension
- Psychogenic non-epileptic seizures (PNES)

C. The Role of Witness Accounts in Defining Seizure Semiology

A reliable witness account is essential to accurately define the event's semiology, as patients often cannot provide accurate historical details due to altered consciousness during the seizure. Witness accounts can help to determine:

- The type of seizure (e.g., focal, generalized)
- The duration of the seizure
- The presence of specific symptoms, such as jerking movements, loss of consciousness, or aura
- The patient's behavior during and after the seizure

D. Characteristics of Generalized Tonic-Clonic Seizures (GTCS)

Generalized tonic-clonic seizures (GTCS), also known as grand mal seizures, are characterized by:

- Stiffening of the body
- Jerking movements of the arms and legs
- Loss of consciousness

GTCS typically follow a consistent pattern of five phases:

1) **Onset**: Sudden loss of consciousness and muscle rigidity
2) **Pre-tonic clonic**: Brief period of muscle twitching
3) **Tonic**: Muscles stiffen and body stiffens
4) **Early clonic**: Rhythmic jerking movements of the arms and legs
5) **Clonic**: Decreasing jerking movements and gradual return of consciousness

E. Characteristics of Focal Seizures

Focal seizures, also known as partial seizures, are characterized by symptoms that originate from a specific area of the brain. They may manifest as:

- Motor seizures: Jerking movements of the arms or legs
- Sensory seizures: Paresthesias, pain, or other abnormal sensations
- Autonomic seizures: Changes in heart rate, blood pressure, or sweating
- Psychic seizures: De´ja` vu, jamais vu, or other mental disturbances

F. Postictal Symptoms

Postictal symptoms, which occur after a seizure, are common and can include:

- Confusion
- Anterograde amnesia (loss of memory for events that occurred during or after the seizure)
- Somnolence or fatigue
- Sore limb muscles
- Hemiparesis (weakness on one side of the body)
- Aphasia (difficulty with language)

G. The Role of Videos in Seizure Diagnosis

Videos of seizures, increasingly captured on digital devices, can provide valuable diagnostic information and improve diagnostic certainty. Videos can help to:

- Confirm the diagnosis of a seizure
- Identify the type of seizure
- Exclude other causes of symptoms

H. The Importance of History and Physical Examination

While video/EEG telemetry remains the gold standard for seizure diagnosis, the history and physical examination are essential initial steps. A thorough history can provide clues about the type of seizure and possible underlying causes. The physical examination can also reveal signs of epilepsy or other neurological conditions.

I. Questions for a Doctor to Fill in Information About a Patient Who May Have Epilepsy

1) Has the patient ever experienced sudden loss of consciousness or awareness?
2) Has the patient noticed any unusual muscle movements, such as jerking or twitching?
3) Has the patient ever had staring spells or episodes of confusion that others have noticed?
4) Has the patient experienced any sensory disturbances, such as strange smells, tastes, or lights?
5) Does the patient have a family history of epilepsy or other neurological disorders?
6) Has the patient experienced any head injuries or trauma in the past?
7) Is the patient taking any medications that could increase the risk of seizures?
8) Does the patient consume caffeine, alcohol, or other substances that could trigger seizure-like symptoms?
9) Has the patient noticed any changes in their sleep patterns or routine?
10) Has the patient experienced any unusual stress or emotional triggers recently?

J. TSA3-D Algorithm

As shown in Fig. 1, the proposed TSA3-D consists of of two input streams: the time-frequency stream and the frequency-space stream. Within each stream, there are the same structure with five blocks. The first block includes: a 3-D convolutional layer, followed by a 3-D batch normalization layer, a ReLU activation function, and a 3-D maxpooling layer. For the 2nd–5th blocks, there are four attention blocks; each block includes two 3-D convolution layers and one 3-D maxpooling layer replaced by the batch normalization. Meanwhile, the 3-D attention module is adopted in the 2nd–5th blocks to achieve discriminative interictal EEGs feature learning. For each stream, a fully connected network is employed to learn the probability of sample belonging to each category. At last, the softmax scores of two streams are fused TABLE III NETWORK ARCHITECTURE OF TSA3-D by averaging to achieve the final classification. The kernel size of each block is $3 \times 3 \times 3$, the stride size for the first block is $1 \times 2 \times 2$, and $2 \times 2 \times 2$ for the rest. The number of filters of the five blocks are 64, 64, 128, 256, and 512, respectively. A summary table of the proposed network's architecture Algorithm is shown in Table III, including the layers and their sizes. Algorithm 1 summarizes the pseudo code of the proposed TSA3-D.

Algorithm 1 TSA3-D-Based Epilepsy Syndrome Classification Input: Interictal EEGs CWT scalograms database M = Mi, Input *XmRDmHmWm* , maximal iterative number K. Interictal EEGs PSD frequency-bands images database N = Ni, Input Xn RDn×Hn×Wn , maximal iterative number K. Output: The training model of TSA3-D. Processing stage: 1) while k K do a) Randomly select a batch interictal EEGs CWT scalograms Mi from M and a batch interictal EEGs frequency bands images Ni from N b) Perform feature extraction on Xm, Xn by forward propagation c) k ← k + 1 2) Calculate the loss loss = 1 n n i=1 m j=1 p(xi j)log(q(xi j)) 3) Compute the loss by back propagation 4) Update the network parameters 5) end while

CONCLUSION

In this article, a novel two-stream attention 3-D convolution structure deep learning model, TSA3-D, has been developed for childhood epilepsy syndrome classification. The study

was carried out on the interictal EEGs of 115 subjects from the Children's Hospital, Zhejiang University School of Medicine (CHZU). The experiments have demonstrated that the proposed TSA3-D model can achieve an impressive overall classification accuracy of 99.52 and outperforms several state-of-the-art (SOTA) algorithms. The study validated several key findings:

1) Interictal EEG data, recorded during the intervals between seizures, are highly applicable for epilepsy syndrome classification. This approach proves to be more feasible and practical than relying on EEGs captured during seizure onset.

2) The transformation of the montage arrangement and the utilization of combined time-frequency/frequency-space features significantly enhance the characterization of EEG data, improving the accuracy of epilepsy syndrome classification.

3) The developed 3-D Channelwise Attention (CA) and Dual Spatial Attention (DSA) blocks are effective in achieving discriminative multichannel EEG feature learning across time, frequency, and spatial representations.

Clinical history played a vital role in this study, enabling a more comprehensive understanding of each subject's epilepsy syndrome. Future research will continue to leverage clinical history and focus on the development of lightweight Deep Neural Networks (DNNs) for childhood epilepsy syndrome classification. These advancements aim to improve the efficiency and accessibility of epilepsy syndrome diagnosis, ultimately benefiting patients and healthcare providers.

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