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Review

Epileptic multi-seizure type classification using electroencephalogram signals from the Temple University Hospital Seizure Corpus: A review

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ABSTRACT

Epilepsy is one of the most paramount neurological diseases, affecting about 1% of the world's population. Seizure detection and classification are difficult tasks and are ongoing challenges in biomedical signal processing to enhance medical diagnosis. This paper presents and highlights the unique frequency and amplitude information found within multiple seizure types, including their morphologies, to aid the development of future seizure classification algorithms. Whilst many published works in the literature have reported on seizure detection using electroencephalogram (EEG), there has yet to be an exhaustive review detailing multi-seizure type classification using EEG. Therefore, this paper also includes a detailed review of multi-seizure type classification performance based on the Temple University Hospital Seizure Corpus (TUSZ) dataset for focal and generalised classification, and multi-seizure type classification. Deep learning techniques have a higher overall average performance for focal and generalised classification compared to machine learning techniques, whereas hybrid deep learning approaches have the highest overall average performance for multi-seizure type classification. Finally, this paper also highlights the limitations of the TUSZ dataset and suggests some future work, including the curation of a standardised training and testing dataset from the TUSZ that would allow a proper comparison of classification methods and spur advancement in the field.

1. Introduction

Epilepsy is one of the most common neurological disorders, affecting roughly 50 million people worldwide (Brodie, Schachter, & Kwan, 2012). For generations, epilepsy has been associated with fear, misunderstanding, discrimination, and societal stigma where epilepsy often leaves patients with a higher rate of physical problems (e.g., fractures and bruising from seizure-related traumas) and it is also associated with multiple psychological problems (e.g., anxiety, depression, and sadness). Moreover, the likelihood of premature death in epileptic patients is up to three times higher compared to the global average (Saab, Dunnmon, Ré, Rubin, & Lee-Messer, 2020; World Health Organisation, 2019).

Several explanations about the origins of the problem have already been proposed. However, the main disruption is thought to be propagated when millions of neurons are synchronously excited, hence causing a wave of electrical activities in the cerebral cortex (Tzallas, Tsipouras, & Fotiadis, 2009). Although many underlying illnesses could potentially lead to epilepsy, the cause of epilepsy remains unclear in roughly half of all global cases. Nevertheless, the known causes can be separated into the following categories: structural, genetic, infectious, metabolic, immune, and unknown (Sazgar & Young, 2019b). With proper diagnosis and administration of anti-seizure medications, up to 70% of patients with epilepsy could live seizure-free. The two most reliable indications of seizure recurrence are a verified etiology of the seizure and an abnormal electroencephalography (EEG) pattern (World Health Organisation, 2019).

An EEG is a non-invasive diagnostic tool that measures cortical activities based on voltage fluctuations with millisecond temporal resolution. Additionally, due to its relatively low cost, EEGs are often utilised in medical research for sleep studies, brain-computer interfaces

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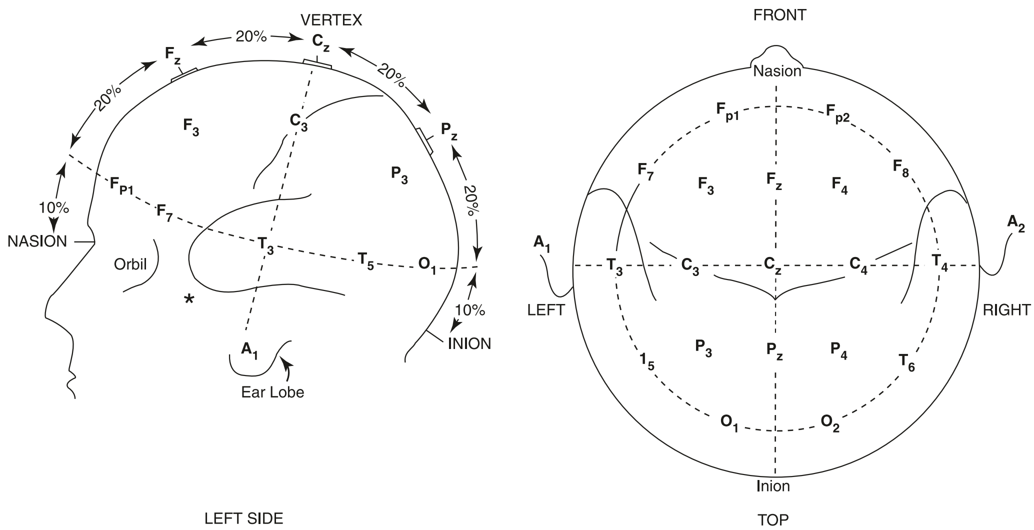

Fig. 1. The International 10–20 System for placements of EEG electrodes (Sazgar & Young, 2019a).

(BCI), as well as seizure detection and classification (Craik, He, & Contreras-Vidal, 2019; Saab et al., 2020). In seizure-related studies, EEGs are used to perform the following purposes:

- Isolate epileptic seizures from non-epileptic seizures, fainting, movement disorders, and various migraine variants
- Potentially help reduce medication dosages
- Determine epileptic or non-epileptic variant for purposes of medication
- Localise cortex region where seizure propagation has occurred

The International 10–20 System is the standard for scalp electrode placement for EEG measurement (see Fig. 1). Intracranial EEGs (iEEG) have also been utilised as they are usually less corrupted by external and internal disturbances and noise commonly encountered when using the International 10–20 System. An iEEG is usually used when results from non-invasive methods proved to be inconclusive. However, being an invasive method, the iEEG is usually used as a last resort as it could cause associated risks such as infections, malignant cerebral edema, hematoma formation, and brain compression resulting from intracranial electrodes (Nagahama et al., 2018).

In 2017, the International League Against Epilepsy (ILAE), which comprises a team of the world's leading epilepsy professionals, introduced a new method to categorise seizure types (Fisher, Cross, D'Souza, et al., 2017). This enables neurologists to more accurately describe and diagnose a patient's seizures, and to assist in prescribing appropriate treatments. Also known as the ILAE 2017 Classification of Seizure Types Checklist, the study presented a general guideline to group seizures based on certain characteristics that occur throughout the event: (i) location of seizure onset, (ii) awareness during the event, and (iii) motor characteristics (see Fig. 2). The location of seizure onset can be further broken down into three main categories: (i) focal onset, (ii) generalised onset, and (iii) unknown onset. Focal onset seizures occur in one hemisphere of the brain and are recognised by whether awareness during the event is retained or impaired as shown in Fig. 2 (Fisher, Cross, D'Souza, et al., 2017). As for generalised onset seizures, they occur throughout most, if not all, of the brain rapidly and it is also common for patients to lose consciousness or to have involuntary muscle spasms (Roy, Asif, Tang, & Harrer, 2020). Of all known generalised onset seizure types, tonic-clonic seizures are the most recognisable where the patient becomes stiff followed by involuntary jerking movements (Epilepsy Society, 2018c). As for unknown onset seizures, they are defined as seizures that are either unusual and do not fit into other categories (usually due to insufficient information to classify as one of the defined seizure types), or they have been missed by the clinicians (Epilepsy Society, 2018c).

Fig. 2 also provides a comprehensive overview of the motor and non-motor characteristics that occur during these seizure onsets. Patients generally experience one type of seizure, although it is also possible for some patients to experience multiple types of seizures. Furthermore, the type of seizures that a patient experience may change over time (National Institute for Health and Care Excellence, 2020).

Traditionally, manual inspection of EEGs for epileptic seizures is performed by board-certified EEG interpreters, who must observe patients over a specific period of time. This process is costly and time consuming, especially when observing EEG signals recorded over an extended duration of time. This can also place significant physical and mental strains on physicians as EEG recordings typically span several hours, with many patients being watched overnight or even for days (Saab et al., 2020). Furthermore, manual inspection of long EEG recordings may be subject to human error. As a result, substantial effort and research have been invested into the design and development of high-accuracy state-of-the-art seizure detection and classification algorithms to help alleviate the clinical burden of traditional EEG analysis (Ahmedt-Aristizabal et al., 2020; Asif, Roy, Tang, & Harrer, 2020; Daoud & Bayoumi, 2019; Dissanayake, Fernando, Denman, Sridharan, & Fookes, 2021; Hussein et al., 2019; J. et al., 2020; Khosla, Khandnor, & Chand, 2021; Özdamar & Kalayci, 1998; Reuben et al., 2020; Roy et al., 2020; Shahbazi & Aghajan, 2018; Shakeel et al., 2021; Shoeibi et al., 2021; Sriraam et al., 2018; Wang et al., 2017).

Basic seizure detection systems (yes or no cases) have been used for decades, and their complexity surged after the digital EEG era (Dissanayake et al., 2021; Li et al., 2020; Sun et al., 2019; Varsavsky, Mareels, & Cook, 2016; Yuan, Xun, Jia, & Zhang, 2019; Zhou et al., 2018). Seizure classification algorithms based on EEGs were developed later, which typically consist of the following steps (see Fig. 3):

1. *EEG signal preprocessing*: A notch filter is commonly used to remove the 50–60 Hz electrical noise interference and often a band-pass filter with varied ranges is also used to limit artefact (Dash, Kolekar, & Jha, 2020).
2. *Feature extraction*: Various time- and frequency-domain as well as time–frequency features are typically extracted.
3. *Feature selection*: Independent component analysis (ICA), principal component analysis (PCA), and other statistical methods are often used to reduce and select key features for classification.
4. *Seizure classification*: Common machine learning techniques such as linear discriminant analysis (LDA), support vector machines

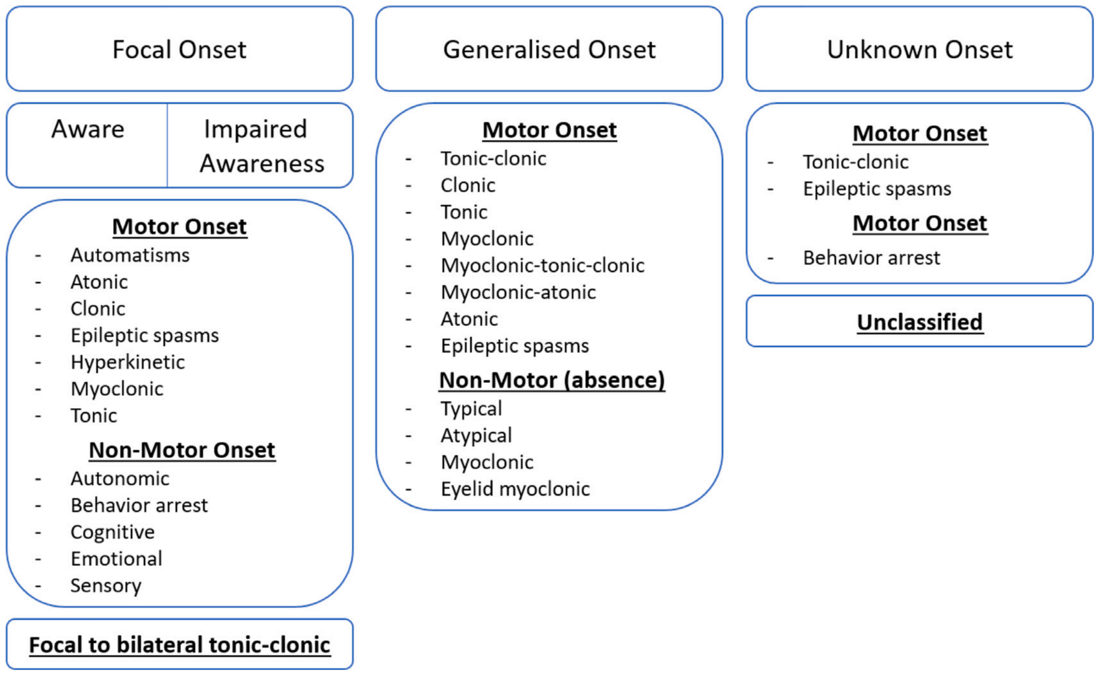

Fig. 2. The ILAE 2017 Classification of seizure types checklist (Fisher, 2017).

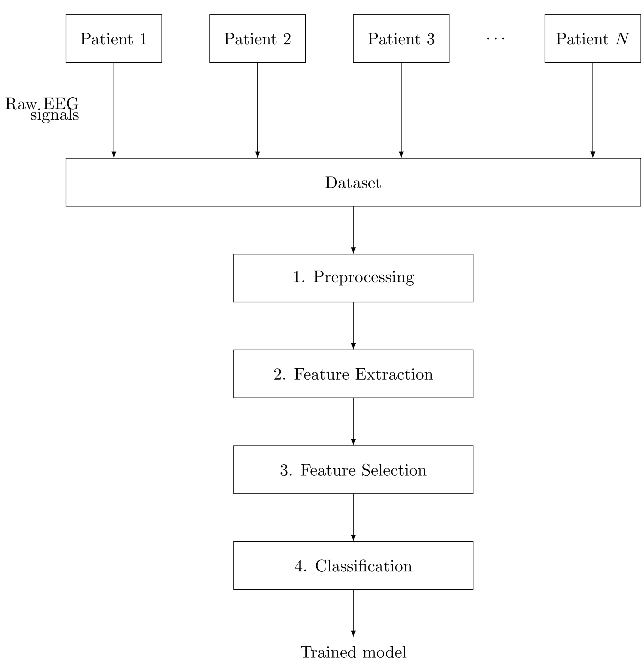

Fig. 3. A general schematic of a seizure classification algorithm.

(SVM), decision trees (DT), and deep learning approaches such as convolutional neural networks (CNN) are used for classification of seizure types (Shoeibi et al., 2021).

Based on published literature, traditional machine learning approaches such as SVM and k-nearest neighbours (k-NN) can achieve state-of-the-art accuracies for seizure detection (Jaiswal & Banka, 2018; McCallan et al., 2021; Shoeb & Guttag, 2010; Zhang et al., 2022). However, these techniques achieve lower accuracies with possibilities of false positive for seizure classification (Kim et al., 2020). To overcome these shortcomings, the use of deep learning techniques such as CNN (Acharya, Oh, Hagiwara, Tan, & Adeli, 2018; Raghu, Sriraam, Temel, Rao, & Kubben, 2019; Zhou et al., 2018), recurrent neural networks (RNN) (Einizade, Mozafari, Sardouie, Nasiri, & Clifford, 2020), and long short-term memory (LSTM) networks (Baghdadi et al., 2021; Hu, Yuan, Xu, Leng, Yuan, & Yuan, 2020; Shahbazi & Aghajan, 2018) for seizure classification have gained much attention in recent times due to the advancements and affordability of graphics processing units (GPUs) and the accessibility to larger and higher quality datasets.

Multi-seizure type classification is crucial in epilepsy research for a number of reasons. It enables personalised treatment plans, leading to better seizure control. Grouping patients based on seizure types aids in selecting appropriate therapies, including those approved specifically for certain seizure types. Furthermore, it helps focus research on understanding the mechanisms and characteristics of different seizure types, facilitating the development of targeted interventions (Fisher, Cross, French, et al., 2017). However, several findings have proved insufficient for use in clinical settings as a result of the unique presentation of epileptic episodes in EEG (Cao, Yao, Chen, Sun, & Tan, 2021). Nevertheless, despite the limitations posed by the unique presentation of epileptic episodes in EEG recordings, significant strides have been made in the field of multi-seizure type classification. Many researchers have contributed to the development of advanced algorithms with the explicit goal of achieving applicability in clinical settings (Albaqami, Hassan, & Datta, 2022; Roy et al., 2020; Saputro et al., 2019; Shakeel et al., 2021). These endeavours will be explored in greater detail in Section 4, where the research and methodologies behind accurate and effective seizure type classification will be thoroughly discussed.

Given the ongoing interest in the field to continually enhance the accuracy of automated seizure diagnosis, this paper serves to review state-of-the-art multi-seizure type classification studies published since 2018. Studies focused on seizure detection are omitted since there exist many recent review papers summarising such work (Boonyakitanont, Lek-Uthai, Chomtho, & Songsiri, 2020; Craik et al., 2019; Kim et al., 2020; Siddiqui, Morales-Menendez, Huang, & Hussain, 2020). Furthermore, this review focuses on research using scalp EEG databases, specifically the Temple University Hospital (TUH) EEG Seizure Corpus (TUSZ) dataset since it is the only open-source EEG dataset that contains annotations of multiple seizure types (Shah et al., 2018).

This paper is organised as follows: Section 2 defines the seizure and non-seizure states, and summarises the multiple seizure types

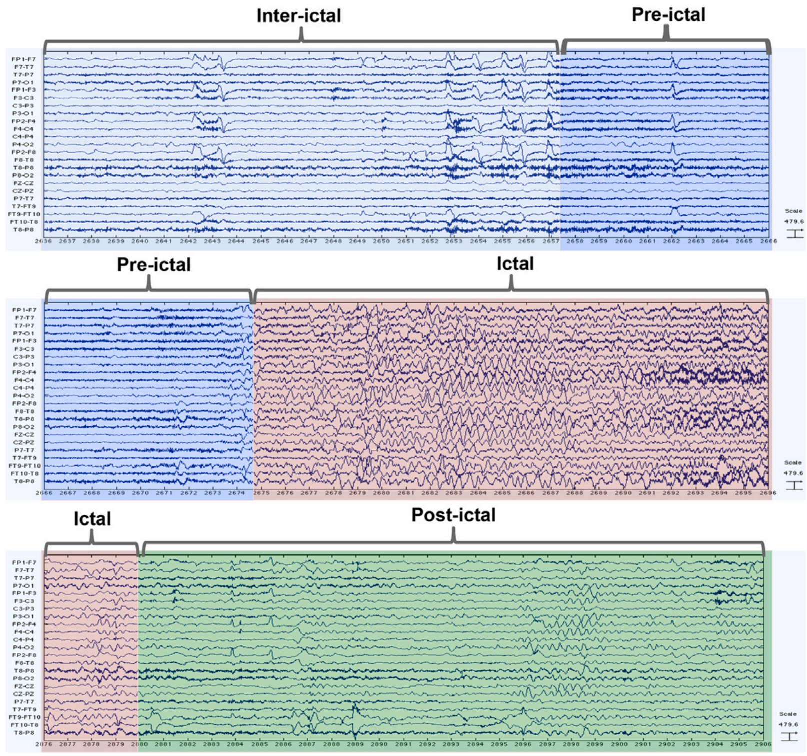

Fig. 4. EEG signals of a patient with epileptic seizure and the onsets of the 4 states (pre-ictal, ictal, post-ictal, and inter-ictal) (Moghim & Corne, 2014).

and their individually associated morphologies according to the ILAE 2017 Classification of Seizure Types Checklist (Fisher, Cross, D'Souza, et al., 2017). Section 3 details the open-source TUSZ dataset. Section 4 reviews and compares the methods proposed for focal and generalised classification and multi-seizure type classification. Finally, a conclusion is provided in Section 5, where the main limitations of the TUSZ dataset are discussed, together with the suggestion of some future work.

2. Seizure semiology

2.1. Seizure and non-seizure states

Based on EEG signals of epileptic patients, four states or periods can be commonly identified: *ictal*, *pre-ictal*, *post-ictal*, and *inter-ictal*. These ictal states refer to the specific periods of a seizure episode, when mood and behavioural changes can occur as a result. The ictal states are usually brief, lasting less than three minutes. They are known to begin and end abruptly and can be associated with other ictal phenomena, such as oral and motor automatisms (Foong, 2017). The pre-ictal state is the state before the seizure occurs whilst the post-ictal state is the altered state of consciousness after the seizure, which can last between 5–30 minutes (Pillai & Sperling, 2006). The inter-ictal state is the time between seizures when brain activities are more nominal, i.e. non-pre- and non-post-ictal states. The pre-ictal and inter-ictal states can vary significantly from one patient to another (Zhang, Guo, Yang, Chen, & Lo, 2019). Fig. 4 depicts an example of the EEG signals and the onsets of the various states.

Having better knowledge and understanding about these different states of a seizure episode and to use them to predict a seizure event several minutes before its onset (i.e., seizure prediction) is crucial for seizure management (Kuhlmann, Lehnertz, Richardson, Schelter, & Zaveri, 2018). This holds particularly true for patients who have not attained full seizure control. The advancement of a technique that can predict seizures with high accuracy has the potential to significantly improve therapeutic options and, as a result, enhance the quality of life for people with epilepsy. It should be acknowledged that the data selection can affect the results (Mormann, Andrzejak, Elger, & Lehnertz, 2007). Consequently, much interests have been focused on the identification of the pre-ictal state (Usman et al., 2019). Published research have reported many methodologies for seizure prediction over the years (Bandarabadi, Teixeira, Rasekhi, & Dourado, 2015; Daoud & Bayoumi, 2019; Dissanayake et al., 2021; Hosseini, Soltanian-Zadeh, Elisevich, & Pompili, 2016; Hussein et al., 2019; Ibrahim et al., 2019; Khan, Marcuse, Fields, Swann, & Yener, 2017; Reuben et al., 2020; Zhang et al., 2019). However, achieving a high sensitivity rate of classification between the inter-ictal and pre-ictal states whilst limiting false positives remains an ongoing challenge.

2.2. Seizure types

This section summarises the various seizure types and their individually associated morphologies. Example EEG waveform of the seizure types are plotted in the supplementary Figures S1.1–S1.15.

2.2.1. Focal Aware Seizures (FAS)

Focal seizures are one of the most prevalent forms of seizure amongst epileptic patients. Having being known as simple partial seizures since 1981, it has since been renamed as focal aware seizures (FAS) by ILAE in 2017 (Fisher, Cross, D'Souza, et al., 2017). The FAS are described as seizures that occur in a focal area whilst the patient is still in a state of awareness. Hence, the patient is alert and will remember the seizure occurrence. However, people who experience FAS may find it difficult to describe the seizure episode, e.g., they may say that they felt strange and somewhat distressed during the episode (Epilepsy Society, 2018c). The FAS are thought to affect about 6–12% of epilepsy patients and they are commonly linked with other forms of seizures. There has been no indication of a predisposition towards gender, race, or ethnicity. However, incidents of FAS occurrences have been on the rise amongst the elderly population, in particular those with cerebrovascular disease (Kumar, Maini, Arya, & Sharma, 2022). Figure S1.1 shows an EEG recording of a FAS.

2.2.2. Focal Impaired Awareness Seizures (FIAS)

Previously known as complex partial seizures, focal impaired awareness seizures (FIAS) affect a greater area of one hemisphere (side) of the brain compared to FAS. Another characteristic of the FIAS is that they directly affect the patient's ability to respond to any stimuli as the patient is rendered unaware of their current situation. During one of these seizures, the patient may appear to be confused or react in an abnormal manner (Epilepsy Society, 2018b). FIAS are also the most prevalent seizure type, affecting approximately 36% of epileptic patients in all age groups after the first year of infancy, where they are most commonly found in children and the elderly. However, there is no evidence of a predisposition for gender or race. In some cases, FIAS could develop after FAS (or sometimes also called 'auras') (Kumar & Sharma, 2022). Before awareness is impaired, these auras can last from a few seconds to 1–2 min. FIAS can also include involuntary movements called 'automatisms' such as hands-rubbing, lip-smacking, and chewing movements, which persist longer than 30 s, usually ranging from 1–2 min up to 10 min. Symptoms of absence seizures can mimic those of FIAS. However, generalised 3 Hz spike-wave complexes will be visible on the ictal EEG. The symptoms of focal seizures with reduced consciousness vary, depending on where they occur in the brain. The temporal lobe is the source of most FIAS. Extratemporal origin has been documented in 10–30% of reported cases (Danzer, 2019; Kumar & Sharma, 2022). Figures S1.2–S1.4 depict EEGs presented with FIAS.

2.2.3. Atonic seizures

The physiological meaning of atonic is lacking muscular tone, where a patient loses their leg tone and drops (HarperCollins Publishers Ltd, 2022). As a result, atonic seizure is also commonly known as *drop attack*. Other causes of atonic seizures include myoclonic, tonic, and myoclonic-atonic seizures (Fisher, Cross, D'Souza, et al., 2017; International League Against Epilepsy (ILAE), 2021b). Atonic seizures are usually very brief, lasting less than 2 s (International League Against Epilepsy (ILAE), 2021b). However, this is disputed as it has also been reported that the maximum duration recorded was around 15 s (Epilepsy Foundation, 2020). Atonic seizures can have motor characteristics that involve the limbs, head, or trunk, and are often associated with intellectually impairment individuals (International League Against Epilepsy (ILAE), 2021a). Over the years, this seizure type has been renamed multiple times; it was also called *akinetic seizures* and *astatic seizures* (Rolston, Englot, Wang, Garcia, & Chang, 2015). Atonic seizures are present in many different forms, such as Lennox–Gastaut Syndrome (LGS) (Patil, 2007) or Dravet syndrome (Cedars Sinai, 2020), where atonic seizures usually occur alongside other forms of seizures such as tonic-clonic seizures. Atonic seizures occur more often in children and are rare in adulthood, with roughly 1–3% of the population diagnosed with the disorder (The Hospital for Sick Children (SickKids), 2020). The spike-and-wave complexes of atonic seizures can be grouped into a frequency range of 1–4 Hz (Swaiman et al., 2017). Before the occurrence of a spike-wave complex, slowing may be prevalent at 1–2 Hz, after which a more irregular spike-wave would form (Foldvary-Schaefer & Wyllie, 2007; International League Against Epilepsy (ILAE), 2021b). Atonic seizures are different from tonic in that there is no convulsion as the body goes limp and not stiff. This lack of muscle artefact means that the seizure is more clearly seen in the patient's EEG.

2.2.4. Tonic seizures

According to ILAE, tonic seizures are characterised by a few seconds to minutes of prolonged increase in muscle contraction. However, based on existing studies, an episode of tonic seizure usually lasts 10–20 s (Fisher, Cross, D'Souza, et al., 2017; Tatum IV, 2014). Tonic seizures can have a focal or a generalised onset where the focal causes eyelid or neck flexion and the generalised onset causes tonic bilateral limb movements often with neck stiffening (Roger, 2005). Generalised tonic seizures can also vary in their intensity and they usually occur during a state of consciousness. However, this state of consciousness may be impaired during an episode. Tonic seizures involve some types of prolonged muscle stiffening; axial tonic seizures (paraspinal stiffening), axorhizomelic tonic seizures (stiffening of the proximal area of legs and arms), and global tonic seizures (stiffening of the entire body). Just like atonic seizures, this seizure type is most commonly associated with intellectual impairment and the Lennox–Gastaut syndrome (Fisher, Cross, D'Souza, et al., 2017; Holmes, 1997). A recent study in 2018 shows that 14% out of 270 patients ranging from one month old to 90 years old had generalised tonic seizures, with 3% of those showing as focal during the start of the episode (Fernandez-Baca Vaca, Mayor, Losarcos, Park, & Lüders, 2018). In adults, tonic seizures usually have a sudden onset with a rhythm at 10 Hz, with generalised paroxysmal fast activity associated with anterior and vertex regions (International League Against Epilepsy (ILAE), 2021b). Low amplitude and fast frequency information may also be found in the background of an EEG during a tonic seizure episode (Tatum IV, 2014). As a result, this seizure type may be difficult to distinguish from dystonic activity or non-epileptic discharges (Abend, Jensen, Inder, & Volpe, 2018; Fisher, Cross, D'Souza, et al., 2017). The 'slow-flat-slow' pattern in the EEG is defined by a slow phase where delta waves appear and the wave amplitude rises, followed by a rapid flattening of the EEG that have stronger lower frequency components, and a slow phase during which normal brain activity returns. The greater the duration of this slow-flat-slow pattern during the pre-ictal stage, the greater the possibility of muscular movements (Solbiati & Sheldon, 2014). This pre-ictal and post-ictal slow-flat-slow features, alongside bilateral synchronous spikes of 10–25 Hz with medium to high amplitude, are the most important features to help define tonic seizures (Foldvary-Schaefer & Wyllie, 2007; Holmes, 1997). Also, there is an attenuation towards the frontal region of the brain. Hence, the channels used for analysis and diagnosis could be reduced (Holmes, 1997). Figures S1.5–S1.7 show examples of EEGs with tonic seizure.

2.2.5. Clonic seizures

Clonic seizure is another type of motor seizure that involves body movements and is characterised by sustained bilateral rhythmic jerking with loss of consciousness, usually lasting between 30–60 s (Tatum IV, 2014). It may be difficult to differentiate clonic seizures from repetitive serial myoclonic seizures, although the rhythmic jerking and consciousness of the patient may provide an insight to distinguish between the two seizure types (International League Against Epilepsy (ILAE), 2021b). Clonic seizures exhibit strong and quick movements, where these muscle jerks can be observed in an EEG (Velíšková & Velíšek, 2017). Clonic seizures are always the last seizure type when paired with one or more other seizure types. This characteristic is largely due to the slowing that is present at the end of the clonic seizure, which have a 1–3 Hz rhythm with decreasing frequency and an increase in amplitude over time (Pisani & Spagnoli, 2019). Synchronous spike-wave activity is usually seen in the ictal state of a clonic seizure, which is most apparent in the rolandic region (Tatum IV, 2014). Focal clonic seizures commonly occur in the central region of the brain and it is very rare that generalised clonic seizures will occur after early infancy. Clonic seizures start in the fore-brain, which indicates that it will show in any of the central sensors (Velíšková, 2006). The rate for clonic seizure has not been well documented as it is usually mixed in with some other seizure types, but the percentage of epileptic patients who have this seizure type is about 12% (Young Epilepsy, 2021).

2.2.6. Tonic-clonic seizures

Tonic-clonic seizures are the mostly commonly known seizure type, where the body is in convulsion and the patient is incoherent. This seizure type also exhibits recruiting rhythm, which are repetitive α frequencies in the maximal anterior region. Tonic-clonic seizures can occur at any age, but rarely during infancy (Tatum IV, 2014). Generalised tonic-clonic seizures are associated with loss of consciousness and are symmetric, bilateral generalised motor seizures. They have a tonic period (prolonged increase in muscle contraction) followed by a clonic period (sustained rhythmic jerking). However, this can vary as other variations (e.g., myoclonic-tonic-clonic and clonic-tonic-clonic) have also been found. Generalised fast rhythmic spikes can be seen in the tonic stage, although this may be obscured by artefacts (muscular movements), and bursts of spikes and slows waves occur during the clonic period. During the post-ictal period, irregular slow activity can often be noted. Localisation of tonic-clonic seizures may differ with each seizure (International League Against Epilepsy (ILAE), 2021b). In genetic generalised epilepsy, tonic-clonic seizures may occur without a focal onset. Mygenic artefact may interfere with the EEG before decrescendo phasic movement artefact from the clonic period, which ends before post-ictal suppression occurs (Tatum IV, 2014). Figures S1.8–S1.11 show tonic-clonic seizure in EEG recordings.

2.2.7. Myoclonic seizures

Myoclonic seizures are very sudden, usually lasting less than 350 ms, where brief muscular contractions occur causing a fast jerking motion (Striano & Belcastro, 2012). Nevertheless, some reports have noted that myoclonic seizures could have a duration ranging from 0.5–2 s (Nijsen, Cluitmans, Griep, & Aarts, 2006). Myoclonic seizures are most prevalent in childhood, although this seizure type can appear at any age. Myoclonic seizures range in their distribution and intensity of manifestations and can have either focal or generalised onset. A single complex, generalised spike-and-wave activity, or a burst of diffuse polyspike-and-wave activity is usually observed in the EEG (International League Against Epilepsy (ILAE), 2021b). Sometimes, myoclonic seizures can also be observed alongside other types of seizures such as myoclonic-atonic, myoclonic absence, or myoclonic-tonic seizures (Tatum IV, 2014). They can be found in a variety of epilepsy syndromes, including idiopathic generalised epilepsies (IGEs) such as benign myoclonic epilepsy of infancy or juvenile myoclonic epilepsy (JME), epileptic encephalopathies such as Dravet syndrome (DS), and progressive myoclonic epilepsies. A patient's sleep cycle can be disrupted since it is common to have multiple myoclonic seizures throughout the night (Striano & Belcastro, 2012). Figures S1.12–S1.13 show EEGs with myoclonic seizures.

2.2.8. Absence seizures

According to the Epilepsy Society, there are two main forms of absence seizures: typical absence and atypical absence seizures (Epilepsy Society, 2018a). In addition, there are also other forms of absence seizures such as myoclonic absence, absence with myoclonia of the eyelids, and childhood absence epilepsy (CAE). The ILAE defines typical absence seizures as non-motor seizures with a generalised onset and are characterised by a sudden loss of movement and consciousness. This seizure type is most commonly observed in childhood and can occur frequently as shown in Figures S1.14–S1.15. Absence seizures start and finish abruptly, and they usually have fewer complex automatisms than FIAS. However, it is more likely that some awareness is retained in adolescents. As a result, EEG data is frequently required for diagnosis as typical absence seizures are easily missed because they are usually brief and cause the patient to be passive and unresponsive for a few seconds (International League Against Epilepsy (ILAE), 2021b). Absence seizures may include clonic movements (e.g., eyelid, eyebrow, head, or chin movements), usually at around 3 Hz. Myoclonic movements could also occur, but only in rare cases. In childhood absence epilepsy, regular 3 Hz generalised spike-and-wave activity can be observed on the EEG (Lüders et al., 1998). For absence seizures in adolescence, a rapid irregular 3.5–6 Hz generalised spike-and-wave and polyspike-and-wave activity should be observed. Should a slow spike-and-wave (i.e. < 2.5 Hz) occur, the seizure is more likely to be an atypical absence seizure, which has a less abrupt onset and offset of loss of awareness. Figure S1.14 shows an EEG presenting an absence seizure (International League Against Epilepsy (ILAE), 2021b).

2.2.9. Unclassified and unknown seizures

The ILAE defined a seizure as unknown seizures if the onset is not witnessed. This could be due to a multitude of reasons, i.e. the patient is alone or asleep, or the observer is too distracted by the seizure occurrence to identify any key defining onset features. However, if key characteristics are observed during a seizure, the ILAE allows the seizure to be classified as having a focal or generalised onset when there is a high degree of confidence in the accuracy of the determination ($>$ 80%). Otherwise, the seizure should remain unknown until more information becomes available. Following additional diagnostics or clinical data, seizures in this group are frequently reclassified as focal or generalised onset seizures (Fisher, Cross, D'Souza, et al., 2017). On the other hand, a seizure may be impossible to classify due to insufficient information or the odd character of the seizure, in which case it is referred to as an unclassified seizure. Unclassified classification should only be used in unusual circumstances, such as when the physician is certain that the occurrence is a seizure but is unable to identify it further (Fisher, Cross, D'Souza, et al., 2017).

3. Epileptic seizure EEG datasets

The availability of datasets is crucial for the design and development of accurate and reliable seizure classification algorithms. Here, the prominent datasets that have advanced research in this field are discussed.

Seizure datasets (open and non-open source) commonly found in the literature are University of Bonn (Andrzejak et al., 2001), CHB-MIT (Shoeb & Guttag, 2010), Freiburg (University of Freiburg, 2020), Kaggle (Kaggle, 2014), Hauz Khas (Swami, Gandhi, Panigrahi, Tripathi, & Anand, 2016), Flint-Hills Scientific (FHS) (Osorio et al., 2005), Bern-Barcelona (Andrzejak, Schindler, & Rummel, 2012), Zenodo (Stevenson, Tapani, Lauronen, & Vanhatalo, 2018), Epilepsia (Epilepsia, 2020), and TUSZ (Harati, Lopez, Obeid, Picone, Jacobson, & Tobochnik, 2014). However, most of these datasets only provide binary labels to identify whether a patient has had a seizure or not, or they provide labels for seizure prediction, such as different combinations of ictal states (i.e., ictal, pre-ictal, post-ictal, inter-ictal), without specifying the seizure type. The TUSZ dataset is an exception to this.

Furthermore, the University of Bonn dataset consists of a limited number of single-channel recordings (100 recordings from five files), with a short duration of 23.6 s, and three of the five files were collected using iEEG (Andrzejak et al., 2001). This small dataset may not capture the full complexity and variability of seizure activity. The CHB-MIT dataset includes data from a relatively small number of patients (23 patients) within a specific age range (3–22 years), with a majority of the patients being female (Shoeb & Guttag, 2010). The Zenodo dataset only includes EEG recordings of 79 human neonates (Stevenson et al., 2018). These datasets may not be representative of the broader epilepsy population. The Freiburg dataset utilises iEEG signals from 21 patients with refractory focal epilepsy, which may not fully generalise to other seizure types (University of Freiburg, 2020). The Kaggle dataset includes recordings from five dogs and two humans, which might not adequately capture the complexities of human epileptic activity (Kaggle, 2014). The Hauz Khas dataset comprises data from 21 patients, with recordings restricted to focal areas only (Swami et al., 2016). The FHS dataset consists of iEEG recordings also collected from focal areas of 10 patients, limiting the diversity of brain activity captured and possibly not feasible for other seizure types (Osorio et al., 2005). The Bern-Barcelona dataset consists of iEEG recordings from five patients, including three without seizures and two with pharmacoresistant focal-onset epilepsy. However, its limited patient sample size and focus on a specific epilepsy type may limit its applicability to a diverse patient populations (Andrzejak et al., 2012). The Epilepsia database includes data from over 250 patients with epilepsy, including 50 patients with intracranial recordings consisting of up to 122 channels (Epilepsia, 2020). Additionally, although comprehensive, is not open-source and requires payment for access.

As the TUSZ is the only open-source EEG dataset that contains annotations of multiple seizure types, this review considers only notable existing works that utilised the TUSZ. The TUSZ dataset is the largest publicly available dataset of EEG recordings (Harati et al., 2014). The corpus is accessible via the Neural Engineering Data Consortium (NEDC) website (www.nedcdata.org). In addition to the TUSZ dataset, the NEDC provides several other dataset corpora. The TUH EEG Corpus (TUEG) is a comprehensive archive of 26,846 clinical EEG recordings collected over a span of 15 years. The TUH Abnormal EEG Corpus (TUAB) consists of EEGs annotated as normal or abnormal. The TUH EEG Artefact Corpus (TUAR) is a subset of TUEG specifically annotated for five different artefacts (i.e., eye movement, chewing, shivering, electrode pop, electrode static, and lead artefacts, and muscle artefacts). The TUH EEG Epilepsy Corpus (TUEP) comprises recordings from 100 patients with epilepsy and 100 patients without epilepsy, determined by certified neurologists. The TUH EEG Events Corpus (TUEV) contains annotations of EEG segments classified into six different categories (i.e., spike and sharp wave, generalised periodic epileptiform discharges, periodic lateralised epileptiform discharges, eye movement, artefact, and background). Lastly, the TUH EEG Slowing Corpus (TUSL) includes annotations of slowing events. The TUSZ dataset contains over 30,000 clinical scalp EEG recordings collected since 2002 from outpatient care units, intensive care units (ICUs), emergency management units (EMUs), emergency rooms (ERs), and various other hospital centres. The clinical data includes artefacts such as eye blinking and muscle movement, which could be useful for seizure detection and classification. The raw EEG signals are multi-channel recordings, where the number of channels range from 20 and 128 (Harati et al., 2014). The data are digitised using a 16-bit A/D converter and the frequency of the samples ranges from 250 to 1024 Hz. The TUSZ also includes more than 10 different electrode configurations and more than 40 channel configurations (Golmohammadi, Harati Nejad Torbati, Lopez de Diego, Obeid, & Picone, 2019). This dataset can be utilised for both institutional research as well as commercial purposes (Shah et al., 2018). The documentations are compiled and combined with written reports by clinicians on identified patients with their respective EEG scans. These reports contain unstructured text detailing the patients' medical history, medications, and clinical assessments (Obeid & Picone, 2016). Using the clinicians' reports and preliminary analysis of the EEGs, the annotation team could classify multiple seizure types (e.g., absence, myoclonic, tonic-clonic, etc.).[1] A list of the seizure type labels is given in Table 1.

4. Existing studies on seizure classification

This section reviews the notable methods in the literature for seizure classification using EEGs. The papers reviewed in this study were obtained via Google Scholar, specifically those released between 2018 and 2022 from various notable publications, including but not limited to ScienceDirect and IEEE Xplore. The keywords used in our search were "automated epileptic seizure classification", "seizure type classification", "EEG signal", "Temple University Hospital (TUH) Seizure Corpus", "focal and generalised classification", and "multi-classification". The following review is divided into two parts: (i) classification between focal seizure, generalised seizure, and non-seizure, and (ii) multi-seizure type classification for multiple or all seizure types available in the TUSZ. The following are the inclusion criteria for this review:

- Research publications where multi-seizure type classification was employed
- Research publications that utilised the TUSZ
- Research published from 2018 till 2022
- Articles published by reputable publishers, including but not limited to ScienceDirect and IEEE Xplore

The exclusion criteria are as follows:

- Research publications that focused on seizure detection or prediction
- Research published prior to 2018
- Research publications that were not written in English
- Research publications that did not provide exhaustive quantitative performance metrics
- Research published as preprints

As a result, three journal articles and one conference proceedings were selected for the review of focal and generalised seizure classification (see Section 4.1). As for the review of multi-seizure type classification in Section 4.2, 15 journal articles and 14 conference proceedings were selected.

Table 1
The seizure type labels used in the annotated TUSZ (Rahman et al., 2019).

Label	Seizure type	Description
SEIZ	Seizure	Basic annotation for seizures.
FNSZ	Focal non-specific seizure	Seizures occurring in a specific focality.
GNSZ	Generalised non-specific seizure	Seizures occurring throughout the entirety of the brain.
SPSZ	Simple partial seizure	Brief seizures that begin in one part of the brain where the patient is fully aware.
CPSZ	Complex partial seizure	Similar to simple partial seizure but with impaired awareness.
ABSZ	Absence seizure	Sudden and brief seizures involving lapse in attention. Commonly found in children and usually last under 5 s.
TNSZ	Tonic seizure	Seizures involving stiffening of muscles. Commonly, albeit not always linked with tonic-clonic seizures.
TCSZ	Tonic-clonic seizure	This seizure type is often linked with violent muscle contractions and loss of consciousness.
MYSZ	Myoclonic seizure	A seizure occurring with brief involuntary twitching.

4.1. Focal and generalised seizure classification

One of the primary challenges in seizure classification is to determine whether the detected seizures are focal or generalised. The ability to determine the location of epileptic seizures is critical to plan for the best treatment selection and surgical operations. The most efficient and straightforward method to locate the origin of a seizure is through the analysis of EEG signals. Given that visual examination and interpretation of EEGs are time-consuming and require the expertise of qualified experts, there is a need for the design and development of effective automated detection and classification approaches. However, due to the lack of publicly accessible EEG datasets and the complexity of clinical annotations, the ability to automate the process of discriminating seizure types (i.e. focal, generalised, and non-seizure) remains a largely overlooked and technically challenging area.

Mozafari and Sardouie (2019) proposed a method to detect both focal and generalised seizures. Initially, blind source separation (BSS) methods were utilised to reduce the artefacts in the raw EEG signals. Then, the channels were split into two clusters. Thresholding was then applied to each cluster, where the epoch was allocated to determine the seizure class if at least one cluster had seizure activity. The approach achieved 80.72% in accuracy, 80% in sensitivity, 81.08% in specificity, and 67.55% in precision in a mixed generalised and focal seizure dataset.

[1] Some terminologies have changed since this dataset was made publicly available. For example, SPSZ is now referred to as FAS (Fisher, Cross, D'Souza, et al., 2017).

Einizade et al. (2020) suggested an approach for generalised and focal seizure classification using deep RNN and CNN to gather spatial and temporal information at the same time. The proposed method achieved an accuracy of 82%, precision of 71.69%, and sensitivity of 85%.

George, Subathra, Sairamya, Susmitha, and Premkumar (2020) proposed a method for seizure classification based on tunable-Q wavelet transform (TQWT), entropies, particle swarm optimisation (PSO), and artificial neural network (ANN). First, the EEG data were decomposed into sub-bands using TQWT, where the non-linear features including log energy entropy, Shannon entropy, and Stein's unbiased risk estimate (SURE) entropy were estimated from each sub-band. After that, PSO was used to select the informative features from the computed feature vectors, which were then used as input into an ANN for classification. Their normal-focal-generalised classification had an accuracy of 88.8%.

Sarić, Jokić, Beganović, Pokvić, and Badnjević (2020) achieved the highest accuracy score for focal and generalised seizure classification in this review, where they established a field-programmable gate array (FPGA) based solution to perform classification. The proposed method used a feed-forward multi-layer neural network architecture (MLP ANN), of which five key features were extracted from the EEG data using time-frequency analysis, followed by the continuous wavelet transform (CWT) and statistical analysis. Using k-fold cross-validation, appropriate parameters of the ANN model were then identified. This model was coded in very high-speed integrated circuit hardware description language (VHDL) on an FPGA and real-time classification was performed with the best performing ANN model. The accuracy achieved from this investigation was 95.14% with the 5-12-3 MLP ANN configuration.

4.2. Multi-seizure type classification

Multi-seizure type classification is an ongoing major challenge that is further complicated by the following factors:

1. Several types of seizures have been proven to exhibit similar clinical and EEG symptoms, and it has been reported that even the most experienced neurologists encounter difficulties in distinguishing between focal and generalised seizures (Mozafari & Sardouie, 2019).
2. Under certain circumstances and conditions where long-term monitoring is required (e.g., video-EEG monitoring that can continue for days), neurologists and medical support staff must devote a significant amount of time, effort, and concentration to manually analyse lengthy EEG recordings to ensure an accurate diagnosis (Saab et al., 2020).
3. Signal interpretation is known to have a poor inter-rater concordance, i.e. it depends entirely on the individual expert's level of experience and diagnosis skills.
4. Inter-subject variability results in a wide range of interpretations of the same seizure type amongst multiple patients, and sometimes even for the same person over time.
5. Signal artefacts in various forms obstruct accurate diagnosis (Albaqami et al., 2022).

To ensure optimal treatment, it is critical to classify each patient's epilepsy with the correct seizure type. If the seizure type is misclassified, the treatment prescribed by the clinician may not assist in reducing the impact of the seizure on the patient's overall health conditions, but could also potentially make them worse. Furthermore, an accurate identification of seizure type is critical as it may be able to aid clinicians to predict the likely course of seizure disorders as well as the best pharmaceutical or surgical treatment options (Epilepsy Foundation, 2022).

Saputro et al. (2019) classified three seizure types – GNSZ, FNSZ, TCSZ – alongside non-seizure (NNSZ) using SVM. The training set consisted of 120 data files (20 GNSZ, 50 FNSZ, 25 TCSZ, and 25 NNSZ), and the testing set consisted of 90 data files (20 GNSZ, 50 FNSZ, 5 TCSZ, and 15 NNSZ). Feature extraction was performed using a combination of mel-frequency cepstral coefficients (MFCC), Hjorth descriptor, and ICA. The MFCC and Hjorth descriptor combination achieved the best results with 90.25%, 97.83%, and 91.40% for average sensitivity, average specificity, and accuracy, respectively.

Raghu et al. (2019) proposed a CNN-based framework to classify seven seizure types – SPSZ, CPSZ, FNSZ, GNSZ, ABSZ, TNSZ, TCSZ – as well as NNSZ. First, the EEG data were transformed into spectrogram stacks and fed into the CNN. The performance of the eight-class classification problem was then investigated (and the accuracy recorded) using four CNN models: AlexNet (84.06%), VGG16 (79.71%), VGG19 (76.81%), and the basic CNN model (82.14%).

Song, Aguilar, Herb, and Yoon (2019) proposed a parallel hidden Markov model (PaHMM), which is a simplified dynamic Bayesian modelling approach, to characterise temporal fluctuations of cortical functional connectivity patterns computed using EEG signals. This method achieved a classification accuracy of over 81% for seven different seizure types — FNSZ, GNSZ, SPSZ, CPSZ, ABSZ, TNSZ, and TCSZ.

Wijayanto, Hartanto, Nugroho, and Winduratna (2019) presented a study to classify four seizure types – FNSZ, GNSZ, SPSZ, TNSZ – where features extraction was performed using empirical mode decomposition (EMD) with five levels of intrinsic mode functions (IMFs). The mean, variance, skewness, kurtosis, standard deviation, and interquartile range were then computed. Classification was performed using SVM with five-fold cross validation. The highest accuracy achieved was 95% using quadratic SVM kernel.

Roy et al. (2020) performed a thorough search space exploration to assess the effectiveness of a variety of preprocessing approaches, machine learning algorithms, and hyperparameters to classify seven seizure types — SPSZ, CPSZ, FNSZ, GNSZ, ABSZ, TNSZ, and TCSZ. They achieved a weighted F1 score of up to 0.901 for seizure-wise cross validation and 0.561 for patient-wise cross validation.

A novel hybrid bilinear deep learning network was investigated by Liu, Truong, Nikpour, Zhou, and Kavehei (2020). Short-time Fourier transform (STFT) of 1 s EEG was used to train hybrid bilinear models based on two types of feature extractors, namely CNNs and RNNs. Bilinear pooling was utilised to further investigate second-order features based on interactions between these spatio-temporal variables, which were then employed to classify eight seizure types — SPSZ, CPSZ, FNSZ, GNSZ, ABSZ, MYSZ, TNSZ, and TCSZ. This method achieved a weighted F1 score of 0.974.

Iešmantas and Alzbutas (2020) suggested an approach where eight seizure types were considered, including clonic seizures whilst excluding myoclonic. Feature extraction was performed via brain synchronisation and power spectrum, after which a CNN was applied. In this study, various deep learning methods were investigated. The classifier achieved a sensitivity and specificity of 0.68 and 0.67, respectively.

Tang, Zhao, and Wu (2020) suggested a method to classify seizure types, where raw EEG signals were decomposed into intrinsic frequency bands by wavelet packet decomposition (WPD). Local detrended fluctuation analysis (L-DFA) was applied to these sub-bands to characterise their dynamical fractal structure. SVM was used to classify the seizure types based on the combined fractal spectrum features. The method achieved a total classification accuracy of 97.80%.

A novel EEG seizure classification approach was developed by Ahmedt-Aristizabal et al. (2020) using the main TUSZ with the IBM TUSZ preprocessed data. Traditional deep learning approaches using CNN and RNN with altered architectures using external memory modules with trainable neural plasticity were investigated. This method achieved a weighted F1 score of 0.945.

Asif et al. (2020) presented SeizureNet, a deep learning approach with multi-spectral feature embedding using an ensemble architecture for multi-seizure type classification. SeizureNet achieved a weighted F1 score of 0.95.

Raghu, Sriraam, Temel, Rao, and Kubben (2020) proposed a method to classify SPSZ, CPSZ, FNSZ, GNSZ, ABSZ, TNSZ, TCSZ, and NNSZ. All 19 common channels were selected and transformed into spectrogram stacks that were fed into a CNN. Two scenarios were utilised: (1) Transfer learning with a pre-trained network and, (2) Image feature extraction using a pre-trained network and SVM classification. Ten pre-trained networks where chosen: Alexnet, Vgg16, Vgg19, Squeezenet, Googlenet, Inceptionv3, Densenet201, Resnet18, Resnet50, and Resnet101. For scenario two, the highest classification accuracy achieved was 82.85% and 88.30% using Googlenet and Inceptionv3, respectively.

Li et al. (2020) suggested an end-to-end EEG multi-seizure type classification framework using a novel channel-embedding spectral–temporal squeeze-and-excitation network (CE-stSENet) with a maximum-mean-discrepancy based information maximising loss. Classification accuracy and weighted F1 score was 92% and 0.937, respectively for seven seizure types.

Shakeel et al. (2021) proposed an early diagnosis and management (EDM) system to aid neurologists to classify five classes of seizure types using the TUSZ. Feature extraction was performed using the discrete wavelet transform (DWT) after which k-NN was applied for classification. Validation was performed using 31 patient records with a classification accuracy, sensitivity, and specificity of 97.7%, 92.9%, and 98.7%, respectively, for patient-wise cross validation.

Basri and Arif (2021) classified three seizures types – GNSZ, FNSZ, and CPSZ – as well as NNSZ, collected from the temporal central parasagittal (TCP) average reference (AR) EEG montage system using features extracted from Fast Fourier Transform (FFT). A variety of methods, including the synthetic minority over-sampling technique (SMOTE) and adaptive synthetic (ADASYN) sampling technique, were employed to under-sample the majority class and over-sample the minority classes due to the uneven distribution of the classes. The RF classifier was used, attaining a multi-seizure type classification accuracy of 96%.

Priyasad, Fernando, Denman, Sridharan, and Fookes (2021) proposed a novel deep learning approach with attention-driven data fusion. In this technique, each channel of the EEG data was passed through a deep convolutional network consisting of SincNet and Conv1D layers without any prior preprocessing. Features were therefore learned directly from the input data, thus increasing model interpretability. This method obtained an average weighted F1 score of 0.967.

Tang et al. (2021) utilised a diffusion convolutional recurrent neural network (DCRNN) for automated seizure classification using self-supervised pre-training. This methodology was based on the pairwise distance between electrodes, resulting in a universal undirected and weighted graph. The best results achieved was a weighted F1 score of 0.749 using DCRNN distance graph with pre-training.

Shankar, Dandapat, and Barma (2021b) developed a deep learning approach to classify CPSZ, GNSZ, SPSZ, TCSZ, and NNSZ where images were generated from the EEG data using Gramian angular summation field (GASF), after which they were fed into a CNN. Classification accuracy obtained for the following combinations: (1) CPSZ, SPSZ, and TCSZ, (2) GNSZ, SPSZ, TCSZ, and NNSZ, and (3) CPSZ, GNSZ, SPSZ, NNSZ, and TCSZ, were 89.91%, 84.19%, and 84.20%, respectively, with respective weighted F1 scores of 0.90, 0.84, and 0.84.

Albaqami, Hassan, and Datta (2021) compared wavelet-based feature extraction methods, namely WPD, DWT, and dual-tree complex wavelet transform (DTCWT). Multi-seizure type classification was performed using LightGBM. Three distinct experiments of statistical feature selection methods were then applied. Experiment one examined the mean absolute value, average power, standard deviation, and ratio of the absolute mean values of adjacent coefficients. Experiment two examined the mean absolute value, average power, skewness, and kurtosis. Experiment three examined the mean absolute value, average power, standard deviation, ratio of the absolute mean values of adjacent coefficients, skewness, and kurtosis. Three distinct combinations of seizure types were used for the investigation (two classes, five classes, and seven classes, respectively). However, the combination utilising two classes of seizure types was dedicated for seizure detection studies, hence it is not relevant in this review. In the remaining combinations utilising five classes and seven classes of seizure types, experiment one using DTCWT performed best with a weighted F1 score of 0.958 and 0.899, respectively.

Cao et al. (2021) introduced a domain-invariant deep feature representation approach based on adversarial learning, which allows hybrid deep networks (HDN) to consistently classify seizure types. Feature extraction was performed by labelling multi-lead EEG short samples to train squeeze-and-excitation networks (SENet) during the training phase. Then, the compressed samples were labelled to train LSTM to extract long-term features and construct a classifier during the test phase. Feature mapping of LSTM by adversarial learning between LSTM and clustering subnet was adjusted during the inference phase such that the EEG of the patient and the EEG in the database follow the same deep feature space distribution. Finally, the adjusted classifier was used to determine the seizure type. A seizure classification accuracy of 94.70% was achieved for NNSZ, FNSZ, GNSZ, and CPSZ seizure types.

Shankar, Dandapat, and Barma (2021a) used machine learning classifiers such as ANNs, DTs, k–NN, Random Forest (RF), and eXtreme boosting gradient (XGBoost) to classify CPSZ, FNSZ, GNSZ, and NNSZ. Statistical quantities such as mean, skewness, kurtosis, standard deviation, approximation entropy, and energy were used as features. Furthermore, the classification of seizure types was investigated using the PCA methodology, with smaller dimensions of the feature set. It was reported that the proposed method achieved a classification accuracy of up to 100%.

Through the use of recurrence plots (RPs), Khosla et al. (2021) proposed an automatic machine learning-based multi-seizure type classification approach using six seizure types — ABSZ, FNSZ, CPSZ, GNSZ, TCSZ, and MYSZ. Two methodologies were implemented: (i) a common approach using recurrence quantification analysis (RQA), and (ii) a hybrid method that combines unthresholded recurrence plot with fractal weighted local binary pattern (URP-FWLBP). In both approaches, an indirect variation of SVM (one-vs-rest approach) was employed as the multi-class classifier. The RQA technique produced an accuracy and weighted F1 score of 94.3% and 0.791, respectively, whilst the hybrid URP-FWLBP technique produced an accuracy and weighted F1 score of 100.0% and 1.00, respectively.

Thundiyil, Thungamani, and Hariprasad (2021) classified seven seizure types — GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TNSZ, and TCSZ. They utilised spectrogram images, correlation coefficient based images, mutual information based images, and stacked images. The spectrogram images were classified using Alexnet, whereas the remaining techniques were classified using Resnet18. The highest results from the investigation were achieved using ResNet18 architecture using the mutual information based images, with an accuracy of 97.89%.

Albaqami et al. (2022) presented a novel automatic technique that extracted specific features from epileptic seizures' EEG signals using DTCWT to classify seven seizure types — SPSZ, CPSZ, FNSZ, GNSZ, ABSZ, TNSZ, and TCSZ. Multi-seizure type classification was performed using LightGBM. The EEG signals were decomposed into four levels using DTCWT, after which statistical features were extracted from each coefficient. Utilising five classes (SPSZ, CPSZ, ABSZ, TNSZ, and TCSZ) and seven classes (SPSZ, CPSZ, FNSZ, GNSZ, ABSZ, TNSZ, and TCSZ) of seizure types, the model achieved a weighted F1 score of 0.991 and 0.960, respectively.

Other methodologies reported in the literature include the variable weight CNNs (VWCNNs), which are a type of network structure that uses dynamic weights instead of static weights in its convolutional and fully-connected layers. VWCNNs adapt to a variety of input data properties and can be thought of as an infinite number of fixed-weight CNNs. Jia, Lam, and Althoefer (2022) proposed VWCNNs to classify seven seizure types — FNSZ, GNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ, and NNSZ. Utilising the variable-weight ResNet18 v2 model, the proposed technique achieved a weighted F1 score of 0.94.

Peng et al. (2022) classified four seizure types — combined focal (SPSZ, CPSZ), ABSZ, TNSZ, and TCSZ. They suggested a slim deep neural network based on EEGNet. The first convolution layer of EEGNet was enhanced using a sinusoidal encoding temporal information augmentation module. The study obtained a seizure classification weighted F1 score of 0.758.

Davidson et al. (2022) proposed a novel parallel classifier – Parallel Genetic Naive Bayes (NB) Seizure Classifier (PGNBSC) using five seizure types – combined focal (SPSZ, CPSZ), ABSZ, MYSZ, TNSZ, and TCSZ. EMD was utilised, where the first IMF was extracted and 13 different features were collected from the IMF of each EEG channel. Optimisation of the NB classifier was performed using a genetic algorithm (Binary Grey Wolf Optimisation, Option 1), resulting in a classification accuracy of 85%.

Shankar, Dandapat, and Barma (2022) classified five seizures types – GNSZ, FNSZ, SPSZ, CPSZ, TCSZ – as well as NNSZ. Hilbert Vibration Decomposition (HVD) was employed, after which, vertically stacked CWT images were generated from the first three derived subcomponents. Multi-seizure type classification was performed using a combination of CNN and LSTM, with a classification accuracy and weighted F1 score of 98.82% and 0.988, respectively.

Dang, Shao, Chen, and Yang (2022) classified eight seizure types — GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, MYSZ, TNSZ, and TCSZ. Firstly, the Mean Absolute Spectrum (MAS) features were extracted from raw EEG signals. For feature selection, the relief technique was employed, after which, conversion into images was performed. The highest results were gathered using transfer learning multi-model classification probability fusion, which uses a combination of pre-trained models (Alexnet, Googlenet, Inception-v3, Resnet18, Vgg16, and Vgg19), and SVM. This method obtained a classification accuracy and weighted F1 score of 98.48% and 0.976, respectively.

Zhang et al. (2022) presented an approach based on signal decomposition and statistical methods. The seven seizure types classified in their study were FNSZ, GNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ, and NNSZ. First, the EEG signals were decomposed using the variational mode decomposition (VMD) technique to extract the components of IMFs. For each extracted IMF component, the statistical approach was then used to calculate eight properties, i.e. maximum, minimum, average, variance, skewness, kurtosis, coefficient of variation, and volatility index. Finally, optimal combinations of the features were utilised for classification using non-linear twin support vector machine (NLTWSVM). For multi-seizure type classification, the weighted F1 score achieved was 0.923.

4.3. Comparison of methodologies

4.3.1. Focal and generalised seizure classification

There are only a small number of research papers found in the literature that focus on focal and generalised seizure type classification. Table 2 summarises the performance of the methods employed in four publications consisting of three journal articles and one conference proceedings. The highest accuracy recorded was 95.14% for deep learning using ANN (Sarić et al., 2020). Machine learning was only utilised in one paper, with a classification accuracy of 80.72% (Mozafari & Sardouie, 2019). Overall, the average accuracy achieved using deep learning (Einizade et al., 2020; George et al., 2020; Sarić et al., 2020) was 88.65%.

4.3.2. Multi-seizure type classification

In this study, 29 publications (15 journal articles and 14 conference proceedings) were analysed for multi-seizure type classification, where 17 of those publications employed deep learning and 12 papers utilised machine learning. Fig. 5 summarises the classification methods utilised for multi-seizure type classification, which shows that SVM was used by five publications and CNN was used by seven publications, making them the most popular machine learning and deep learning methodologies, respectively. Additionally, eight hybrid deep learning classification techniques were also used for multi-seizure type classification, suggesting that hybrid deep learning approaches may be a future trend in algorithm development. For all methods that utilised deep learning, the highest accuracy of 98.82% and weighted F1 score of 0.988 were achieved using the hybrid CNN and LSTM approach (Shankar et al., 2022). For machine learning, the highest accuracy of 100% and weighted F1 score of 1.00 were achieved using the URP-FWLBP approach with SVM (Khosla et al., 2021). Overall, machine learning techniques achieved an average accuracy of 95.27% and an average weighted F1 score of 0.938, whereas deep learning only techniques achieved an average accuracy of 87.09% and an average weighted F1 score of 0.895. Additionally, deep learning techniques that utilised a hybrid approach achieved an average accuracy of 96% and an average weighted F1 score of 0.933. Therefore, on average, the machine learning techniques outperformed the pure deep learning techniques, but the hybrid deep learning techniques slightly outperformed the machine learning techniques based on average accuracy results only. Several factors contribute to this finding. Firstly, deep learning models typically necessitate a substantial volume of high quality annotated data for effective training. For instance, Shankar et al. (2021b) employed a mere 18 patients for analysis, and solely utilised data collected from the AR montage system. Moreover, only 60% of this data was allocated for training, resulting in a test accuracy of 84.20% and a weighted F1 score of 0.84. This highlights the significant impact of data quality and quantity on the performance of deep learning models. Whereas, Priyasad et al. (2021) used 215 patient files for their deep learning model and were able to obtain an accuracy of 96.70%. Conversely, machine learning techniques can yield satisfactory results even with smaller datasets and can benefit from the feature extraction stages. For example, Shakeel et al. (2021) incorporated 31 patients and achieved an accuracy of 97.70%. Secondly, deep learning models exhibit great complexity and computationally costly properties, requiring significant computer resources for both training and testing. In contrast, machine learning methods frequently provide easier and more computationally effective options (Ahmad et al., 2022). Hybrid deep learning approaches demonstrate that the amount of annotated data has a reduced impact compared to pure deep learning. Hybrid deep learning models combine multiple architectures to improve generalisation and classification performance by utilising complex representation learning. They address limitations of large annotated datasets in deep learning and complex feature extraction techniques necessary in machine learning, resulting in enhanced performance for complex data. For instance, in the study by Shankar et al. (2022), despite using only 30 files, high performance was achieved with an accuracy of 98.82% and a weighted F1 score of 0.988. This trend holds even with a larger amount of annotated data, as demonstrated by Liu et al. (2020) who utilised 314 files and achieved a weighted F1 score of 0.974. Table 3 summarises the performance (accuracy, weighted F1 score, sensitivity, and specificity) of the methods presented in the papers reviewed.

Fig. 6 shows that the most common seizure type classified was GNSZ, whereas the least common seizure type classified was MYSZ. Fig. 6 also shows the average accuracy and weighted F1 score from all the techniques that used each specific class. Classifications involving MYSZ have the highest average accuracy. However, due to the scarcity of its use, we will consider classifications that included FNSZ to have the highest average accuracy at 94.23%. The highest average weighted F1 score of 0.951 was achieved by classifications that included NNSZ.

Table 2
Methods used for focal, generalised, and non-seizure classification using scalp EEG signals from the TUSZ. The best result recorded is highlighted in bold.

Publications	Features	Classifier	Performance
Mozafari and Sardouie (2019)	BSS, Clustering	LDA	Accuracy: 80.72% Precision: 67.55% Sensitivity: 80.00% Specificity: 81.08%
Einizade et al. (2020)	ICA, Canonical correlation analysis (CCA)	Deep RNN and CNN	Accuracy: 82.00% Precision: 71.69% Sensitivity: 85.00%
George et al. (2020)	TQWT, Entropies, PSO	ANN	Accuracy: 88.80%
Sarić et al. (2020)	CWT	FPGA-based implementation of 5-12-3 MLP ANN	Accuracy: **95.14%**

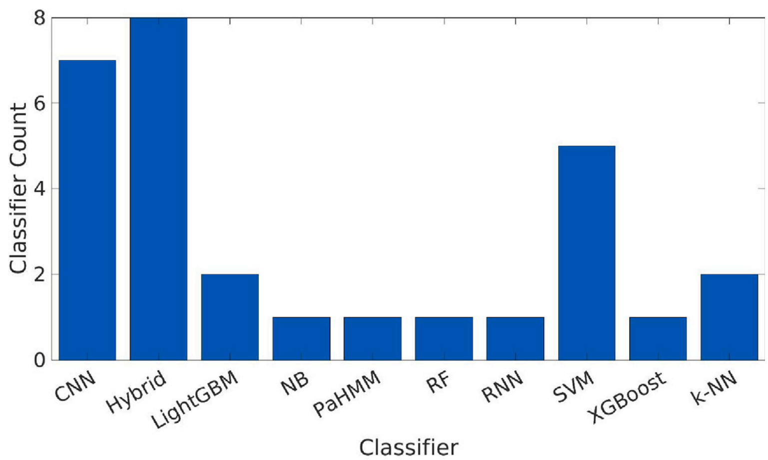

Fig. 5. Total counts for each classification method used for multi-seizure type classification from the reviewed publications.

Direct comparison of individual performance of the methods in these 29 papers is challenging because there are only a few common set of seizure types classified and a few common performance metrics reported. Tables 4 and 5 list the common performance metrics of studies for seven common classes (seven seizure types) and eight common classes (seven seizure types and one non-seizure), respectively. For papers that reported classification of the seven common classes, the average weighted F1 score achieved using deep learning (Ahmedt-Aristizabal et al., 2020; Jia et al., 2022; Li et al., 2020; Thundiyil et al., 2021) and machine learning (Albaqami et al., 2021, 2022; Roy et al., 2020; Zhang et al., 2022) were 0.951 and 0.921, respectively. The highest weighted F1 score achieved using deep learning was 0.980 with the Resnet18 method (Thundiyil et al., 2021), and 0.960 using machine learning with the LightGBM technique (Albaqami et al., 2022). Therefore, for the classification of the seven common classes, deep learning techniques outperformed the machine learning techniques on average. For the classification of the eight common classes, the highest accuracy obtained was 97.80% using SVM (Tang et al., 2020).

4.4. Limitations and future work

There are two main inherent limitations of the TUSZ dataset that affect the accuracy of multi-seizure type classification. Firstly, there is an issue of class imbalance, where non-seizure data is more numerous than seizure data. This could result in biased classifiers. In order to address this issue, various strategies have been employed. In the first strategy, the sample size of the majority class is decreased by undersampling. Examples of this method can be found in Basri and Arif (2021), Iešmantas and Alzbutas (2020). The second strategy oversamples the minority classes in the dataset, hence boosting the sample size. This can be carried out using a specified selection criteria or through random sampling. Oversampling is one of the most common resampling methods used, with many research groups incorporating it into their studies (e.g., Basri & Arif, 2021; George et al., 2020; Shankar et al., 2021b). The impact of asymmetrical data can also be overcome by generating synthetic data. Common examples of synthetic data generators include but are not limited to SMOTE (Chawla, Bowyer, Hall, & Kegelmeyer, 2002), borderline SMOTE (Han, Wang, & Mao, 2005), and ADASYN sampling approach (He, Bai, Garcia, & Li, 2008). Currently, only one research publication has addressed the class imbalance issue using synthetic methods for multi-seizure type classification, where the ADASYN approach had the greatest outcome (Basri & Arif, 2021).

Secondly, there exist three EEG montage systems in the TUSZ. There are two unipolar montages (the Linked Ear (LE) reference and Average Reference (AR)) and a bipolar montage (the bipolar Temporal Central Parasagittal (TCP)). Detailed specifications for the various montage system orientations are outlined by Ferrell et al. (2020). Each EEG data in the database was recorded using one of the two unipolar montages. It is worth noting that the AR A is a subgroup of the AR unipolar montage, with only 20 EEG channels and excluding electrodes A1 and A2.

Among the analysed publications, 10 did not specify the montage system used (Cao et al., 2021; Iešmantas & Alzbutas, 2020; Peng et al., 2022; Roy et al., 2020; Saputro et al., 2019; Shakeel et al., 2021; Song et al., 2019; Tang et al., 2020; Thundiyil et al., 2021; Zhang et al., 2022). Among the remaining publications, 11 utilised a unipolar montage system (Davidson et al., 2022; Khosla et al., 2021; Liu et al., 2020; Priyasad et al., 2021; Raghu et al., 2019, 2020; Shankar et al., 2021a, 2021b, 2022; Tang et al., 2021; Wijayanto et al., 2019), with three selecting the AR montage system (Shankar et al., 2021a, 2021b, 2022) and two using the LE montage system (Khosla et al., 2021; Wijayanto et al., 2019). Additionally, eight publications employed a bipolar montage system (Ahmedt-Aristizabal et al., 2020; Albaqami

Table 3
Existing methods for multi-seizure classification using scalp EEG signals from the TUSZ.

Publications	Seizure types	Features	Classifier	Acc.	Sens.	Weighted F1 score	Spec.
Saputro et al. (2019)	FNSZ, GNSZ, TCSZ, NNSZ	MFCC, Hjorth Descriptor, ICA	SVM	91.40%	90.25%	N/A	97.83%
Raghu et al. (2019)	SPSZ, CPSZ, FNSZ, GNSZ, ABSZ, TNSZ, TCSZ, NNSZ	Spectrogram stacks	AlexNet VGG16 VGG19 Basic CNN models	84.06% 79.71% 76.81% 82.14%	N/A	N/A	N/A
Song et al. (2019)	FNSZ, GNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ	14 functional ROIs and Pearsons Correlation Coefficients	PaHMM	81.00%	N/A	N/A	N/A
Wijayanto et al. (2019)	FNSZ, GNSZ, SPSZ, TNSZ	EMD and statistics	Quadratic SVM	95.00%	N/A	N/A	N/A
Roy et al. (2020)	FNSZ, GNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ	FFT	k-NN SGD XGBoost CNN (ResNet50)	N/A	N/A	0.901 0.807 0.866 0.722	N/A
Liu et al. (2020)	FNSZ, GNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ, MYSZ	STFT	Hybrid Bilinear Model	N/A	N/A	0.974	N/A
Iešmantas and Alzbutas (2020)	FNSZ, GNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ, Clonic	Combination of PLV, energy, entropy	CNN	N/A	68.00%	N/A	67.00%
Tang et al. (2020)	FNSZ, GNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ, NNSZ	WPD and L-DFA	SVM	97.80%	N/A	N/A	N/A
Ahmedt-Aristizabal et al. (2020)	FNSZ, GNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ	FFT	NMN	N/A	N/A	0.945	N/A
Asif et al. (2020)	FNSZ, GNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ, NNSZ	Saliency-encoded spectrograms	SeizureNet	N/A	N/A	0.950	N/A
Raghu et al. (2020)	SPSZ, CPSZ, FNSZ, GNSZ, ABSZ, TNSZ, TCSZ, NNSZ	Spectrogram	CNN (Googlenet) CNN (Inceptionv3)	82.85% 88.30%	N/A	N/A	N/A
Li et al. (2020)	ABSZ, FNSZ, GNSZ, CPSZ, SPSZ, TNSZ, TCSZ	Raw EEG	CE-stSENet	92.00%	N/A	0.937	N/A
Shakeel et al. (2021)	ABSZ, FNSZ, GNSZ, CPSZ, NNSZ	DWT	k-NN	97.70%	92.90%	N/A	98.70%
Basri and Arif (2021)	FNSZ, GNSZ, CPSZ, NNSZ	FFT with SMOTE FFT with ADASYN	RF	96% 96.20%	N/A	0.960 0.961	N/A
Priyasad et al. (2021)	SPSZ, CPSZ, FNSZ, GNSZ, ABSZ, TNSZ, TCSZ, NNSZ	Raw EEG	Deep learning architecture with attention-driven data fusion	N/A	N/A	0.967	N/A
Tang et al. (2021)	Combined focal (CF) seizures, GNSZ, ABSZ, and combined tonic (CT) seizures	FFT and statistics	DCRNN distance graph with pre-training	N/A	N/A	0.749	N/A
Shankar et al. (2021b)	3–5 classes: GNSZ, SPSZ, CPSZ, TCSZ, NNSZ	GASF	CNN	89.91% (3 classes) 84.19% (4 classes) 84.20% (5 classes)	N/A	N/A	N/A
Albaqami et al. (2021)	5 classes (SPSZ, CPSZ, ABSZ, TNSZ, TCSZ) 7 classes (GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ)	WPD, DWT, DTCWT	LightGBM	N/A	N/A	0.958 (DTCWT, 5 classes) 0.899 (DTCWT, 7 classes)	N/A
Cao et al. (2021)	NNSZ, FNSZ, GNSZ, CPSZ	Raw EEG	HDN	94.70%	N/A	N/A	N/A
Shankar et al. (2021a)	NNSZ, CPSZ, FNSZ, GNSZ	Statistical variants and PCA	ANN DT k-NN RF XGBoost	100.00%	N/A	0.997 0.998 0.998 0.999 0.999	N/A
Khosla et al. (2021)	FNSZ, GNSZ, CPSZ, TCSZ, ABSZ, MYSZ	RQA measures and RFE-RF URP-FWLBP and LDA	SVM with RBF kernel	94.30 1.000	73.80 100.00%	0.791 1.000	95.30 100.00%
Thundiyil et al. (2021)	GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ	Spectrogram CC based images MI based images Stacked Images	AlexNet Resnet18 Resnet18 Resnet18	97.15% 93.45% 97.89% 95.50%	N/A	0.975 0.936 0.980 0.956	N/A
Albaqami et al. (2022)	5 classes (SPSZ, CPSZ, ABSZ, TNSZ, TCSZ) 7 classes (GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ)	DTCWT	LightGBM	N/A	N/A	0.991 (5 classes) 0.960 (7 classes)	N/A

(continued on next page)

Table 3 (*continued*).

Jia et al. (2022)	GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ	Raw EEG	VWCNNs	N/A	N/A	0.940	N/A
Peng et al. (2022)	Combined focal (SPSZ, CPSZ), ABSZ, TNSZ, TCSZ	Raw EEG	TIE-CE-stSENet	N/A	N/A	0.758	N/A
Davidson et al. (2022)	Combined focal (SPSZ, CPSZ), ABSZ, MYSZ, TNSZ, TCSZ	EMD	PGNBSC	85%	N/A	N/A	N/A
Shankar et al. (2022)	GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TCSZ	HVD, CWT stacks	CNN and LSTM	98.82%	N/A	0.988	N/A
Dang et al. (2022)	GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, MYSZ, TNSZ, TCSZ	MAS Feature Images	Transfer learning multi-model classification probability fusion	98.48%	N/A	0.976	N/A
Zhang et al. (2022)	GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ	VMD and statistical features	NLTWSVM	N/A	N/A	0.923	N/A

Table 4
Methods used for classification of seven common classes (specifically, seven seizure types: GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TNSZ, and TCSZ) and the common performance metrics (weighted F1 score).

Publications	Features	Classifier	Weighted F1 score
Ahmedt-Aristizabal et al. (2020)	FFT	NMN	0.945
Li et al. (2020)	Raw EEG	CE-stSENet	0.937
Roy et al. (2020)	FFT	k-NN	0.901
Albaqami et al. (2021)	DTCWT	LightGBM	0.899
Thundiyil et al. (2021)	MI	Resnet18	0.980
Albaqami et al. (2022)	DTCWT	LightGBM	0.960
Jia et al. (2022)	Raw EEG	CNN	0.940
Zhang et al. (2022)	VMD	SVM	0.923

Table 5
Methods used for classification of eight common classes (specifically, seven seizure types: GNSZ, FNSZ, SPSZ, CPSZ, ABSZ, TNSZ, TCSZ; and one non-seizure type: NNSZ) and the common performance metric (accuracy).

Publications	Features	Classifier	Accuracy
Raghu et al. (2019)	Spectrogram	CNN	84.06%
Tang et al. (2020)	WPD AND L-DFA	SVM	97.80%
Raghu et al. (2020)	Spectrogram	CNN	88.30%

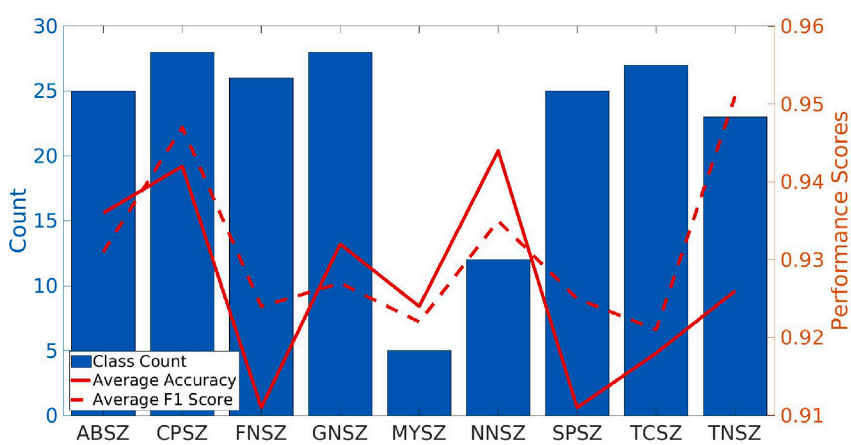

Fig. 6. The total number of times each class (eight seizure types and one non-seizure) was used for classification among the papers reviewed, and the average accuracy and weighted F1 score when the specific class is included for classification.

Table 6
A breakdown of the TUSZ training and testing dataset, file counts for each seizure class, the ratio of the training and testing partition for each seizure class, and the overall ratio of each seizure class within the entire TUSZ dataset.

Dataset	GNSZ	FNSZ	SPSZ	CPSZ	MYSZ	ABSZ	TNSZ	TCSZ
Train file count	187	527	5	134	2	14	9	11
Test file count	56	158	3	35	1	6	19	17
Total file count	243	685	8	169	3	20	28	28
Train data partition (%)	76.95	76.93	62.50	79.29	66.67	70.00	32.14	39.29
Test data partition (%)	23.05	23.07	37.50	20.71	33.33	30.00	67.86	60.71
Overall ratio of seizure class (%)	20.52	57.85	0.68	14.27	0.25	1.69	2.36	2.36

et al., 2021, 2022; Asif et al., 2020; Basri & Arif, 2021; Dang et al., 2022; Jia et al., 2022; Li et al., 2020), with one choosing the AR subgroup available with TUSZ and applying the bipolar TCP montage system to it (Basri & Arif, 2021).

The unipolar montages achieved an average accuracy of 93.48% and a weighted F1 score of 0.935, regardless of the specific TUSZ subgroup used. On the other hand, publications that included the bipolar montage achieved an average accuracy of 95.56% and a weighted F1 score of 0.947, again regardless of the specific TUSZ subgroup used. Comparing these results accurately is challenging due to variations in parameters across different research studies, including differences in seizure type selection and file selection methods. Despite these challenges, the findings suggest that the bipolar TCP montage demonstrated slightly superior performance over the unipolar montage system, with improvements of 2.08% and 1.22% in accuracy and weighted F_1 score, respectively.

Regarding the subgroups within the TUSZ dataset, there is a limited number of publications that have utilised the AR and LE subgroups, making it difficult to draw conclusive findings. However, based on the available research, studies using the AR subgroup, regardless of the montage system, achieved an average accuracy of 98.34% and a weighted F1 score of 0.962. On the other hand, studies that included the LE subgroup achieved an average accuracy of 97.5% and a weighted F1 score of 1, regardless of the specific montage used. It is worth noting that the reported weighted F1 score of 1, indicating perfect performance, is solely based on a single research finding from Khosla et al. (2021) that focused on the LE subgroup. Their study highlighted the benefits of using only the LE reference montage data, which contains less artefacts, resulting in faster training times and higher accuracy results (Khosla et al., 2021). Conversely, Albaqami et al. (2022) used the TCP bipolar montage for its capability to accentuate spikes activity.

Future work should continue to explore how best to deal with the class imbalance and further understand how the classification accuracy of a seizure type depends on the montage. Further advancement in multi-seizure type classification would be greatly facilitated by the availability of a more evenly distributed training and testing dataset, which include the non-seizure and eight seizure-type data, that are curated from the TUSZ. Table 6 outlines a breakdown of the current distribution of classes in the TUSZ dataset, where the FNSZ class makes up over 50% of the entire dataset, and the MYSZ class only accounts for 0.25% of the TUSZ dataset. Furthermore, for the seizure classes TNSZ and TCSZ, there exist more test files than training files, which explains why many paper utilise their own training and testing partition. These standardised datasets would allow a proper comparison of methods developed to classify the nine classes if a common set of performance metrics are reported. Using accurate multi-seizure type classification algorithms, epileptologists would be able to prescribe specific drug treatment to target specific seizure types. Furthermore, accurate seizure type classification could aid researchers in determining the relationship amongst known and unknown syndromes, and the etiologies of the seizure types.

5. Conclusion

This comprehensive review provides a deep understanding of epilepsy and its diagnosis, summarising various seizure types and their characteristics. The review emphasises the use of the TUSZ dataset as the sole online open-source dataset for seizure type classification. It explores the literature on focal and generalised classification, focusing on algorithms utilising the TUSZ dataset. Furthermore, the study analysed 29 publications from 2018 to 2022 on multi-seizure type classification, with 15 journal articles and 14 conference proceedings. The efficacy of pure machine learning, pure deep learning and hybrid deep learning approaches were explored. SVM and CNN were the most popular machine learning and deep learning methodologies, respectively. On average, machine learning techniques outperformed pure deep learning techniques in terms of accuracy and weighted F1 score. However, hybrid deep learning techniques slightly outperformed machine learning techniques based on average accuracy results. Machine learning techniques may potentially outperform deep learning models due to their ability to handle limited annotated data, avoid overfitting and require lower computational resources. Hybrid deep learning models use multiple architectures to improve generalisation and classification performance by harnessing the capabilities of complex representation learning. Limitations were identified, including the selectivity of montage systems (unipolar, and bipolar (TCP)) and subgroups (AR, LE, and AR A) within TUSZ containing different seizure types, leading to variations in the choice of seizure types, files, patients, and performance metrics among researchers. These variations hindered accurate result comparisons. The choice to rely on data from a small number of patients in certain studies could potentially be attributed to the class imbalance associated with the TUSZ dataset, thereby limiting the generalisability of the findings. These variable selection criteria may be influenced by the extensive size of the TUSZ dataset, which encompasses 572 GB.

CRediT authorship contribution statement

Niamh McCallan: Conceptualisation, Methodology, Software, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Scot Davidson:** Writing – review & editing. **Kok Yew Ng:** Conceptualisation, Writing – review & editing, Supervision, Project Administration, Funding acquisition. **Pardis Biglarbeigi:** Writing – review & editing. **Dewar Finlay:** Writing – review & editing. **Boon Leong Lan:** Writing – review & editing. **James McLaughlin:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eswa.2023.121040.

References

Abend, N. S., Jensen, F. E., Inder, T. E., & Volpe, J. J. (2018). Chapter 12 - Neonatal seizures. In J. J. Volpe, T. E. Inder, B. T. Darras, L. S. de Vries, A. J. du Plessis, J. J. Neil, & J. M. Perlman (Eds.), *Volpe's neurology of the newborn* (6th ed.). Elsevier, http://dx.doi.org/10.1016/B978-0-323-42876-7.00012-0, 275 – 321.e14.

Acharya, U. R., Oh, S. L., Hagiwara, Y., Tan, J. H., & Adeli, H. (2018). Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals. *Computers in Biology and Medicine*, *100*, 270–278. http://dx.doi.org/10.1016/j.compbiomed.2017.09.017.

Ahmad, I., Wang, X., Zhu, M., Wang, C., Pi, Y., Khan, J. A., et al. (2022). EEG-based epileptic seizure detection via machine/deep learning approaches: A systematic review. *Computational Intelligence and Neuroscience*, *2022*, http://dx.doi.org/10.1155/2022/6486570.

Ahmedt-Aristizabal, D., Fernando, T., Denman, S., Petersson, L., Aburn, M. J., & Fookes, C. (2020). Neural memory networks for seizure type classification. In *2020 42nd Annual international conference of the IEEE engineering in medicine biology society* (pp. 569–575). http://dx.doi.org/10.1109/EMBC44109.2020.9175641.

Albaqami, H., Hassan, G., & Datta, A. (2021). Comparison of WPD, DWT and DTCWT for multi-class seizure type classification. In *2021 IEEE signal processing in medicine and biology symposium* (pp. 1–7). http://dx.doi.org/10.1109/SPMB52430.2021.9672286.

Albaqami, H., Hassan, G. M., & Datta, A. (2022). Wavelet-based multi-class seizure type classification system. *Applied Sciences*, *12*(11), 5702. http://dx.doi.org/10.3390/app12115702.

Andrzejak, R. G., Lehnertz, K., Mormann, F., Rieke, C., David, P., & Elger, C. E. (2001). Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. *Physical Review E*, *64*(6), Article 061907. http://dx.doi.org/10.1103/PhysRevE.64.061907.

Andrzejak, R. G., Schindler, K., & Rummel, C. (2012). Nonrandomness, nonlinear dependence, and nonstationarity of electroencephalographic recordings from epilepsy patients. *Physical Review E*, *86*(4), Article 046206. http://dx.doi.org/10.1103/PhysRevE.86.046206.

Asif, U., Roy, S., Tang, J., & Harrer, S. (2020). SeizureNet: Multi-spectral deep feature learning for seizure type classification. In *Machine learning in clinical neuroimaging and radiogenomics in neuro-oncology* (pp. 77–87). Springer, http://dx.doi.org/10.1007/978-3-030-66843-3_8.

Baghdadi, A., fourati, R., Aribi, Y., Daoud, S., Dammak, M., Mhiri, C., et al. (2021). *A channel-wise attention-based representation learning method for epileptic seizure detection and type classification*. TechRxiv, http://dx.doi.org/10.36227/techrxiv.17087147.v2.

Bandarabadi, M., Teixeira, C. A., Rasekhi, J., & Dourado, A. (2015). Epileptic seizure prediction using relative spectral power features. *Clinical Neurophysiology*, *126*(2), 237–248. http://dx.doi.org/10.1016/j.clinph.2014.05.022.

Basri, A., & Arif, M. (2021). Classification of seizure types using random forest classifier. *Advances in Science and Technology. Research Journal*, *15*(3), http://dx.doi.org/10.12913/22998624/140542.

Boonyakitanont, P., Lek-Uthai, A., Chomtho, K., & Songsiri, J. (2020). A review of feature extraction and performance evaluation in epileptic seizure detection using EEG. *Biomedical Signal Processing and Control*, *57*, Article 101702. http://dx.doi.org/10.1016/j.bspc.2019.101702.

Brodie, M. J., Schachter, S. C., & Kwan, P. (2012). *Fast facts: Epilepsy*. Karger Medical and Scientific Publishers.

Cao, X., Yao, B., Chen, B., Sun, W., & Tan, G. (2021). Automatic seizure classification based on domain-invariant deep representation of EEG. *Frontiers in Neuroscience*, 1313. http://dx.doi.org/10.3389/fnins.2021.760987.

Cedars Sinai (2020). Atonic seizure with daret syndrome. Retrieved from https://www.cedars-sinai.org/health-library/diseases-and-conditions/a/atonic-seizures.html. (Accessed 21 January 2020).

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*, *16*, 321–357. http://dx.doi.org/10.1613/jair.953.

Craik, A., He, Y., & Contreras-Vidal, J. L. (2019). Deep learning for electroencephalogram (EEG) classification tasks: A review. *Journal of Neural Engineering*, *16*(3), Article 031001. http://dx.doi.org/10.1088/1741-2552/ab0ab5.

Dang, N., Shao, K., Chen, L., & Yang, M. (2022). Multi-model decision-making seizure types classification based on transfer learning. In *2022 International symposium on control engineering and robotics* (pp. 192–201). IEEE, http://dx.doi.org/10.1109/ISCER55570.2022.00040.

Danzer, S. C. (2019). Double agent mTOR. *Epilepsy Currents*, *19*(1), 44–46. http://dx.doi.org/10.1177/1535759718822033.

Daoud, H., & Bayoumi, M. A. (2019). Efficient epileptic seizure prediction based on deep learning. *IEEE Transactions on Biomedical Circuits and Systems*, *13*(5), 804–813. http://dx.doi.org/10.1109/TBCAS.2019.2929053.

Dash, D. P., Kolekar, M. H., & Jha, K. (2020). Multi-channel EEG based automatic epileptic seizure detection using iterative filtering decomposition and hidden Markov model. *Computers in Biology and Medicine*, *116*, Article 103571. http://dx.doi.org/10.1016/j.compbiomed.2019.103571.

Davidson, S., McCallan, N., Ng, K. Y., Biglarbeigi, P., Finlay, D., Lan, B. L., et al. (2022). Epileptic seizure classification using combined labels and a genetic algorithm. In *2022 IEEE 21st mediterranean electrotechnical conference* (pp. 430–435). IEEE, http://dx.doi.org/10.1109/MELECON53508.2022.9843099.

Dissanayake, T., Fernando, T., Denman, S., Sridharan, S., & Fookes, C. (2021). Deep learning for patient-independent epileptic seizure prediction using scalp EEG signals. *IEEE Sensors Journal*, *21*(7), 9377–9388. http://dx.doi.org/10.1109/JSEN.2021.3057076.

Einizade, A., Mozafari, M., Sardouie, S. H., Nasiri, S., & Clifford, G. (2020). A deep learning-based method for automatic detection of epileptic seizure in a dataset with both generalized and focal seizure types. In *2020 IEEE signal processing in medicine and biology symposium* (pp. 1–6). IEEE, http://dx.doi.org/10.1109/SPMB50085.2020.9353629.

Epilepsia (2020). The European epilepsy database. Retrieved from http://epilepsy-database.eu/. (Accessed 17 April 2020).

Epilepsy Foundation (2020). Atonic seizures. Retrieved from https://www.epilepsy.com/learn/types-seizures/atonic-seizures. (Accessed 21 January 2020).

Epilepsy Foundation (2022). Why is classification important?. Retrieved from https://www.epilepsy.com/stories/why-classification-important. (Accessed 30 January 2022).

Epilepsy Society (2018a). Absence seizures. https://epilepsysociety.org.uk/about-epilepsy/epileptic-seizures/absence-seizures. (Accessed 9 December 2021).

Epilepsy Society (2018b). Focal impaired awareness seizures. https://epilepsysociety.org.uk/focal-impaired-awareness-seizures. (Accessed 3 December 2021).

Epilepsy Society (2018c). Seizure types. Retrieved from https://www.epilepsysociety.org.uk/seizure-types#.Xjrtn2j7RPY. (Accessed 6 September 2022).

Fernandez-Baca Vaca, G., Mayor, C. L., Losarcos, N. G., Park, J. T., & Lüders, H. O. (2018). Epileptic seizure semiology in different age groups. *Epileptic Disorders*, *20*(3), 179–188. http://dx.doi.org/10.1684/epd.2018.0970.

Ferrell, S., Mathew, V., Refford, M., Tchiong, V., Ahsan, T., Obeid, I., et al. (2020). The Temple University Hospital EEG corpus: Electrode location and channel labels. *Institute for Signal and Information Processing Report*, *1*(1).

Fisher, R. S. (2017). The new classification of seizures by the international league against Epilepsy 2017. *Current Neurology and Neuroscience Reports*, *17*(6), 48. http://dx.doi.org/10.1007/s11910-017-0758-6.

Fisher, R. S., Cross, J. H., D'Souza, C., French, J. A., Haut, S. R., Higurashi, N., et al. (2017). Instruction manual for the ILAE 2017 operational classification of seizure types. *Epilepsia*, *58*(4), 531–542. http://dx.doi.org/10.1111/epi.13671.

Fisher, R. S., Cross, J. H., French, J. A., Higurashi, N., Hirsch, E., Jansen, F. E., et al. (2017). Operational classification of seizure types by the international league against epilepsy: Position paper of the ILAE commission for classification and terminology. *Epilepsia*, *58*(4), 522–530. http://dx.doi.org/10.1111/epi.13670.

Foldvary-Schaefer, N., & Wyllie, E. (2007). Chapter 52 - Epilepsy. In C. G. Goetz (Ed.), *Textbook of clinical neurology* (3rd ed.). (pp. 1213–1244). Philadelphia: W.B. Saunders.

Foong, J. (2017). *Psychiatric disorders in epilepsy*. EPILEPSY.

George, S. T., Subathra, M., Sairamya, N., Susmitha, L., & Premkumar, M. J. (2020). Classification of epileptic EEG signals using PSO based artificial neural network and tunable-q wavelet transform. *Biocybernetics and Biomedical Engineering*, *40*(2), 709–728. http://dx.doi.org/10.1016/j.bbe.2020.02.001.

Golmohammadi, M., Harati Nejad Torbati, A. H., Lopez de Diego, S., Obeid, I., & Picone, J. (2019). Automatic analysis of EEGs using big data and hybrid deep learning architectures. *Frontiers in Human Neuroscience*, *13*, 76. http://dx.doi.org/10.3389/fnhum.2019.00076.

Han, H., Wang, W.-Y., & Mao, B.-H. (2005). Borderline-SMOTE: A new over-sampling method in imbalanced data sets learning. In *International conference on intelligent computing* (pp. 878–887). Springer, http://dx.doi.org/10.1007/11538059_91.

Harati, A., Lopez, S., Obeid, I., Picone, J., Jacobson, M., & Tobochnik, S. (2014). The TUH EEG CORPUS: A big data resource for automated EEG interpretation. In *2014 IEEE signal processing in medicine and biology symposium* (pp. 1–5). IEEE, http://dx.doi.org/10.1109/SPMB.2014.7002953.

HarperCollins Publishers Ltd (2022). Atonic definition and meaning: Collins English dictionary. URL: https://www.collinsdictionary.com/dictionary/english/atonic. (Accessed 23 July 2022).

He, H., Bai, Y., Garcia, E. A., & Li, S. (2008). ADASYN: Adaptive synthetic sampling approach for imbalanced learning. In *2008 IEEE international joint conference on neural networks* (pp. 1322–1328). IEEE, http://dx.doi.org/10.1109/IJCNN.2008.4633969.

Holmes, G. L. (1997). Chapter 1 - classification of seizures and the epilepsies. In S. C. Schachter, & D. L. Schomer (Eds.), *The comprehensive evaluation and treatment of epilepsy* (pp. 1–36). San Diego: Academic Press, http://dx.doi.org/10.1016/B978-012621355-3/50002-5.

Hosseini, M.-P., Soltanian-Zadeh, H., Elisevich, K., & Pompili, D. (2016). Cloud-based deep learning of big EEG data for epileptic seizure prediction. In *2016 IEEE global conference on signal and information processing* (pp. 1151–1155). IEEE, http://dx.doi.org/10.1109/GlobalSIP.2016.7906022.

Hu, X., Yuan, S., Xu, F., Leng, Y., Yuan, K., & Yuan, Q. (2020). Scalp EEG classification using deep Bi-LSTM network for seizure detection. *Computers in Biology and Medicine*, *124*, Article 103919. http://dx.doi.org/10.1016/j.compbiomed.2020.103919.

Hussein, R., Ahmed, M. O., Ward, R., Wang, Z. J., Kuhlmann, L., & Guo, Y. (2019). Human intracranial EEG quantitative analysis and automatic feature learning for epileptic seizure prediction. arXiv preprint arXiv:1904.03603. http://dx.doi.org/10.48550/arXiv.1904.03603.

Ibrahim, F., El-Gindy, S. A.-E., El-Dolil, S. M., El-Fishawy, A. S., El-Rabaie, E.-S. M., Dessouky, M. I., et al. (2019). A statistical framework for EEG channel selection and seizure prediction on mobile. *International Journal of Speech Technology*, *22*(1), 191–203. http://dx.doi.org/10.1007/s10772-018-09565-7.

Iešmantas, T., & Alzbutas, R. (2020). Convolutional neural network for detection and classification of seizures in clinical data. *Medical & Biological Engineering & Computing*, *58*(9), 1919–1932. http://dx.doi.org/10.1007/s11517-020-02208-7.

International League Against Epilepsy (ILAE) (2021a). Atonic seizure. Retrieved from https://www.epilepsydiagnosis.org/seizure/atonic-overview.html. (Accessed 30 January 2021).

International League Against Epilepsy (ILAE) (2021b). Seizure classification. Retrieved from https://www.epilepsydiagnosis.org/seizure/seizure-classification-groupoverview.html. (Accessed 11 October 2022).

J., P., Subathra, M. S. P., Mohammed, M. A., Maashi, M. S., Garcia-Zapirain, B., Sairamya, N. J., et al. (2020). Detection of focal and non-focal electroencephalogram signals using fast Walsh-Hadamard transform and artificial neural network. *Sensors*, *20*(17), 4952. http://dx.doi.org/10.3390/s20174952.

Jaiswal, A. K., & Banka, H. (2018). Epileptic seizure detection in EEG signal using machine learning techniques. *Australasian Physical & Engineering Sciences in Medicine*, *41*(1), 81–94. http://dx.doi.org/10.1007/s13246-017-0610-y.

Jia, G., Lam, H.-K., & Althoefer, K. (2022). Variable weight algorithm for convolutional neural networks and its applications to classification of seizure phases and types. *Pattern Recognition*, *121*, Article 108226. http://dx.doi.org/10.1016/j.patcog.2021.108226.

Kaggle (2014). American epilepsy society seizure prediction challenge. Retrieved from https://www.kaggle.com/c/seizure-prediction. (Accessed 14 December 2021).

Khan, H., Marcuse, L., Fields, M., Swann, K., & Yener, B. (2017). Focal onset seizure prediction using convolutional networks. *IEEE Transactions on Biomedical Engineering*, *65*(9), 2109–2118. http://dx.doi.org/10.1109/TBME.2017.2785401.

Khosla, A., Khandnor, P., & Chand, T. (2021). EEG based automatic multi-class classification of epileptic seizure types using recurrence plots. *Expert Systems*, Article e12923. http://dx.doi.org/10.1111/exsy.12923.

Kim, T., Nguyen, P., Pham, N., Bui, N., Truong, H., Ha, S., et al. (2020). Epileptic seizure detection and experimental treatment: A review. *Frontiers in Neurology*, *11*, 701. http://dx.doi.org/10.3389/fneur.2020.00701.

Kuhlmann, L., Lehnertz, K., Richardson, M. P., Schelter, B., & Zaveri, H. P. (2018). Seizure prediction—ready for a new era. *Nature Reviews Neurology*, *14*(10), 618–630. http://dx.doi.org/10.1038/s41582-018-0055-2.

Kumar, A., Maini, K., Arya, K., & Sharma, S. (2022). *Simple partial seizure*. Treasure Island (FL): StatPearls Publishing, URL: http://europepmc.org/books/NBK500005.

Kumar, A., & Sharma, S. (2022). *Complex partial seizure*. Treasure Island (FL): StatPearls Publishing, URL: http://europepmc.org/books/NBK519030.

Li, Y., Liu, Y., Cui, W.-G., Guo, Y.-Z., Huang, H., & Hu, Z.-Y. (2020). Epileptic seizure detection in EEG signals using a unified temporal-spectral squeeze-and-excitation network. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *28*(4), 782–794. http://dx.doi.org/10.1109/TNSRE.2020.2973434.

Liu, T., Truong, N. D., Nikpour, A., Zhou, L., & Kavehei, O. (2020). Epileptic seizure classification with symmetric and hybrid bilinear models. *IEEE Journal of Biomedical and Health Informatics*, *24*(10), 2844–2851. http://dx.doi.org/10.1109/JBHI.2020.2984128.

Lüders, H., Acharya, J., Baumgartner, C., Benbadis, S., Bleasel, A., Burgess, R., et al. (1998). Semiological seizure classification. *Epilepsia*, *39*(9), 1006–1013. http://dx.doi.org/10.1111/j.1528-1157.1998.tb01452.x.

McCallan, N., Davidson, S., Ng, K. Y., Biglarbeigi, P., Finlay, D., Lan, B. L., et al. (2021). Seizure classification of EEG based on wavelet signal denoising using a novel channel selection algorithm. In *2021 Asia-pacific signal and information processing association annual summit and conference* (pp. 1269–1276).

Moghim, N., & Corne, D. W. (2014). Predicting epileptic seizures in advance. *PLoS One*, *9*(6), Article e99334. http://dx.doi.org/10.1371/journal.pone.0099334.

Mormann, F., Andrzejak, R. G., Elger, C. E., & Lehnertz, K. (2007). Seizure prediction: The long and winding road. *Brain*, *130*(2), 314–333. http://dx.doi.org/10.1093/brain/awl241.

Mozafari, M., & Sardouie, S. H. (2019). Automatic epileptic seizure detection in a mixed generalized and focal seizure dataset. In *2019 26th National and 4th international Iranian conference on biomedical engineering* (pp. 172–176). IEEE, http://dx.doi.org/10.1109/ICBME49163.2019.9030381.

Nagahama, Y., Schmitt, A. J., Nakagawa, D., Vesole, A. S., Kamm, J., Kovach, C. K., et al. (2018). Intracranial EEG for seizure focus localization: Evolving techniques, outcomes, complications, and utility of combining surface and depth electrodes. *Journal of Neurosurgery*, *130*(4), 1180–1192. http://dx.doi.org/10.3171/2018.1.JNS171808.

National Institute for Health and Care Excellence (2020). *Types of seizures*. NICE, Retrieved from https://www.nice.org.uk/guidance/cg137/ifp/chapter/Types-of-seizure. (Accessed 8 April 2021).

Nijsen, T. M., Cluitmans, P. J., Griep, P. A., & Aarts, R. M. (2006). Short time Fourier and wavelet transform for accelerometric detection of myoclonic seizures. In *EMBS benelux symposium* (pp. 155–158).

Obeid, I., & Picone, J. (2016). The Temple University Hospital EEG data corpus. *Frontiers in Neuroscience*, *10*, 196. http://dx.doi.org/10.3389/fnins.2016.00196.

Osorio, I., Frei, M. G., Sunderam, S., Giftakis, J., Bhavaraju, N. C., Schaffner, S. F., et al. (2005). Automated seizure abatement in humans using electrical stimulation. *Annals of Neurology*, *57*(2), 258–268. http://dx.doi.org/10.1002/ana.20377.

Özdamar, Ö., & Kalayci, T. (1998). Detection of spikes with artificial neural networks using raw EEG. *Computers and Biomedical Research*, *31*(2), 122–142. http://dx.doi.org/10.1006/cbmr.1998.1475.

Patil, A. A. (2007). Lennox-gastaut syndrome. In S. Enna, & D. B. Bylund (Eds.), *XPharm: The comprehensive pharmacology reference* (pp. 1–5). New York: Elsevier, URL: http://www.sciencedirect.com/science/article/pii/B9780080552323606609.

Peng, R., Zhao, C., Jiang, J., Kuang, G., Cui, Y., Xu, Y., et al. (2022). TIE-EEGNet: Temporal information enhanced EEGNet for seizure subtype classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *30*, 2567–2576. http://dx.doi.org/10.1109/TNSRE.2022.3204540.

Pillai, J., & Sperling, M. R. (2006). Interictal EEG and the diagnosis of epilepsy. *Epilepsia*, *47*, 14–22. http://dx.doi.org/10.1111/j.1528-1167.2006.00654.x.

Pisani, F., & Spagnoli, C. (2019). Chapter 7 - Diagnosis and management of acute seizures in neonates. In J. M. Perlman, & M. R. Cilio (Eds.), *Neurology* (3rd ed.). (pp. 111–129). Philadelphia: Content Repository Only!, http://dx.doi.org/10.1016/B978-0-323-54392-7.00007-8, URL: http://www.sciencedirect.com/science/article/pii/B9780323543927000078.

Priyasad, D., Fernando, T., Denman, S., Sridharan, S., & Fookes, C. (2021). Interpretable seizure classification using unprocessed EEG with multi-channel attentive feature fusion. *IEEE Sensors Journal*, *21*(17), 19186–19197. http://dx.doi.org/10.1109/JSEN.2021.3090062.

Raghu, Sriraam, N., Temel, Y., Rao, S. V., & Kubben, P. L. (2019). A convolutional neural network based framework for classification of seizure types. In *2019 41st Annual international conference of the IEEE engineering in medicine and biology society* (pp. 2547–2550). http://dx.doi.org/10.1109/EMBC.2019.8857359.

Raghu, S., Sriraam, N., Temel, Y., Rao, S. V., & Kubben, P. L. (2020). EEG based multi-class seizure type classification using convolutional neural network and transfer learning. *Neural Networks*, *124*, 202–212. http://dx.doi.org/10.1016/j.neunet.2020.01.017.

Rahman, S., Ochal, D., Ferrell, S., Elseify, T., Obeid, I., & Picone, J. (2019). *The Temple University Hospital EEG corpus: Annotation file formats. Philadelphia, Pennsylvania, USA*. The Neural Engineering Data Consortium College of Engineering, Temple University, URL: https://www.isip.piconepress.com/publications/reports/2018/tuh_eeg_annotations. (Accessed 6 September 2022).

Reuben, C., Karoly, P., Freestone, D. R., Temko, A., Barachant, A., Li, F., et al. (2020). Ensembling crowdsourced seizure prediction algorithms using long-term human intracranial EEG. *Epilepsia*, *61*(2), e7–e12. http://dx.doi.org/10.1111/epi.16418.

Roger, J. (2005). *Epileptic syndromes in infancy, childhood and adolescence, Vol. 20*. John Libbey Eurotext.

Rolston, J. D., Englot, D. J., Wang, D. D., Garcia, P. A., & Chang, E. F. (2015). Corpus callosotomy versus vagus nerve stimulation for atonic seizures and drop attacks: A systematic review. *Epilepsy & Behavior*, *51*, 13–17. http://dx.doi.org/10.1016/j.yebeh.2015.06.001.

Roy, S., Asif, U., Tang, J., & Harrer, S. (2020). Seizure type classification using EEG signals and machine learning: Setting a benchmark. In *2020 IEEE signal processing in medicine and biology symposium* (pp. 1–6). IEEE, http://dx.doi.org/10.1109/SPMB50085.2020.9353642.

Saab, K., Dunnmon, J., Ré, C., Rubin, D., & Lee-Messer, C. (2020). Weak supervision as an efficient approach for automated seizure detection in electroencephalography. *NPJ Digital Medicine*, *3*(1), 1–12. http://dx.doi.org/10.1038/s41746-020-0264-0.

Saputro, I. R. D., Maryati, N. D., Solihati, S. R., Wijayanto, I., Hadiyoso, S., & Patmasari, R. (2019). Seizure type classification on EEG signal using support vector machine. *Journal of Physics: Conference Series*, *1201*, Article 012065. http://dx.doi.org/10.1088/1742-6596/1201/1/012065, IOP Publishing.

Sarić, R., Jokić, D., Beganović, N., Pokvić, L. G., & Badnjević, A. (2020). FPGA-based real-time epileptic seizure classification using artificial neural network. *Biomedical Signal Processing and Control*, *62*, Article 102106. http://dx.doi.org/10.1016/j.bspc.2020.102106.

Sazgar, M., & Young, M. G. (2019a). Overview of EEG, electrode placement, and montages. In *Absolute epilepsy and EEG rotation review: Essentials for trainees* (pp. 117–125). Cham: Springer International Publishing, http://dx.doi.org/10.1007/978-3-030-03511-2_5.

Sazgar, M., & Young, M. G. (2019b). Seizures and epilepsy. In *Absolute epilepsy and EEG rotation review: Essentials for trainees* (pp. 9–46). Springer, http://dx.doi.org/10.1007/978-3-030-03511-2_2.

Shah, V., Von Weltin, E., Lopez, S., McHugh, J. R., Veloso, L., Golmohammadi, M., et al. (2018). The Temple University Hospital seizure detection corpus. *Frontiers in Neuroinformatics*, *12*, 83. http://dx.doi.org/10.3389/fninf.2018.00083.

Shahbazi, M., & Aghajan, H. (2018). A generalizable model for seizure prediction based on deep learning using CNN-LSTM architecture. In *2018 IEEE global conference on signal and information processing* (pp. 469–473). IEEE, http://dx.doi.org/10.1109/GlobalSIP.2018.8646505.

Shakeel, S., Afzal, N., Khan, G. H., Khan, N. A., Altaf, M. A. B., et al. (2021). EDM: A multiclassification support system to identify seizure type using K nearest neighbor. In *2021 28th IEEE international conference on electronics, circuits, and systems* (pp. 1–4). IEEE, http://dx.doi.org/10.1109/ICECS53924.2021.9665565.

Shankar, A., Dandapat, S., & Barma, S. (2021a). Classification of seizure types based on statistical variants and machine learning. In *2021 IEEE 18th India council international conference* (pp. 1–6). http://dx.doi.org/10.1109/INDICON52576.2021.9691717.

Shankar, A., Dandapat, S., & Barma, S. (2021b). Seizure type classification using EEG based on gramian angular field transformation and deep learning. In *2021 43rd Annual international conference of the IEEE engineering in medicine & biology society* (pp. 3340–3343). IEEE, http://dx.doi.org/10.1109/EMBC46164.2021.9629791.

Shankar, A., Dandapat, S., & Barma, S. (2022). Seizure types classification by generating input images with in-depth features from decomposed EEG signals for deep learning pipeline. *IEEE Journal of Biomedical and Health Informatics*, http://dx.doi.org/10.1109/JBHI.2022.3159531.

Shoeb, A. H., & Guttag, J. V. (2010). Application of machine learning to epileptic seizure detection. In *Proceedings of the 27th international conference on machine learning* (pp. 975–982).

Shoeibi, A., Khodatars, M., Ghassemi, N., Jafari, M., Moridian, P., Alizadehsani, R., et al. (2021). Epileptic seizures detection using deep learning techniques: A review. *International Journal of Environmental Research and Public Health*, *18*(11), 5780. http://dx.doi.org/10.3390/ijerph18115780.

Siddiqui, M. K., Morales-Menendez, R., Huang, X., & Hussain, N. (2020). A review of epileptic seizure detection using machine learning classifiers. *Brain Informatics*, *7*, 1–18. http://dx.doi.org/10.1186/s40708-020-00105-1.

Solbiati, M., & Sheldon, R. (2014). Syncope: How the EEG helps in understanding clinical findings. *Brain*, *137*(2), 309–311. http://dx.doi.org/10.1093/brain/awt363.

Song, X., Aguilar, L., Herb, A., & Yoon, S.-c. (2019). Dynamic modeling and classification of epileptic EEG data. In *2019 9th International IEEE/EMBS conference on neural engineering* (pp. 49–52). http://dx.doi.org/10.1109/NER.2019.8717126.

Sriraam, N., Raghu, S., Tamanna, K., Narayan, L., Khanum, M., Hegde, A., et al. (2018). Automated epileptic seizures detection using multi-features and multilayer perceptron neural network. *Brain Informatics*, *5*(2), 10. http://dx.doi.org/10.1186/s40708-018-0088-8.

Stevenson, N., Tapani, K., Lauronen, L., & Vanhatalo, S. (2018). *A dataset of neonatal EEG recordings with seizures annotations*. Zenodo, http://dx.doi.org/10.5281/zenodo.4940267.

Striano, P., & Belcastro, V. (2012). Treatment of myoclonic seizures. *Expert Review of Neurotherapeutics*, *12*(12), 1411–1418. http://dx.doi.org/10.1586/ern.12.90.

Sun, C., Cui, H., Zhou, W., Nie, W., Wang, X., & Yuan, Q. (2019). Epileptic seizure detection with EEG textural features and imbalanced classification based on EasyEnsemble learning. *International Journal of Neural Systems*, *29*(10), Article 1950021. http://dx.doi.org/10.1142/S0129065719500217.

Swaiman, K. F., Ashwal, S., Ferriero, D. M., Schor, N. F., Finkel, R. S., Gropman, A. L., et al. (2017). *Swaiman's pediatric neurology E-book: Principles and practice*. Elsevier Health Sciences.

Swami, P., Gandhi, T. K., Panigrahi, B. K., Tripathi, M., & Anand, S. (2016). A novel robust diagnostic model to detect seizures in electroencephalography. *Expert Systems with Applications*, *56*, 116–130. http://dx.doi.org/10.1016/j.eswa.2016.02.040.

Tang, S., Dunnmon, J., Saab, K. K., Zhang, X., Huang, Q., Dubost, F., et al. (2021). Self-supervised graph neural networks for improved electroencephalographic seizure analysis. In *International conference on learning representations*. http://dx.doi.org/10.48550/arXiv.2104.08336.

Tang, L., Zhao, M., & Wu, X. (2020). Accurate classification of epilepsy seizure types using wavelet packet decomposition and local detrended fluctuation analysis. *Electronics Letters*, *56*(17), 861–863. http://dx.doi.org/10.1049/el.2020.1471.

Tatum IV, W. O. (2014). *Handbook of EEG interpretation*. Demos Medical Publishing.

The Hospital for Sick Children (SickKids) (2020). Atonic seizures in children. Retrieved from https://www.aboutkidshealth.ca/Article?contentid=2068&language=English. (Accessed 22 January 2020).

Thundiyil, S., Thungamani, M., & Hariprasad, S. (2021). Big EEG data images for convolutional neural networks. In *2021 IEEE signal processing in medicine and biology symposium* (pp. 1–6). IEEE, http://dx.doi.org/10.1109/SPMB52430.2021.9672272.

Tzallas, A. T., Tsipouras, M. G., & Fotiadis, D. I. (2009). Epileptic seizure detection in EEGs using time-frequency analysis. *IEEE Transactions on Information Technology in Biomedicine*, *13*(5), 703–710. http://dx.doi.org/10.1109/TITB.2009.2017939.

University of Freiburg (2020). Seizure prediction project freiburg. Retrieved from https://epilepsy.uni-freiburg.de/freiburg-seizure-prediction-project/eeg-database. (Accessed 22 May 2020).

Usman, S. M., Khalid, S., Akhtar, R., Bortolotto, Z., Bashir, Z., & Qiu, H. (2019). Using scalp EEG and intracranial EEG signals for predicting epileptic seizures: Review of available methodologies. *Seizure*, *71*, 258–269. http://dx.doi.org/10.1016/j.seizure.2019.08.006.

Varsavsky, A., Mareels, I., & Cook, M. (2016). *Epileptic seizures and the EEG: Measurement, models, detection and prediction*. Taylor & Francis, http://dx.doi.org/10.1201/b10459.

Velíšková, J. (2006). Chapter 48 - Behavioral characterization of seizures in rats. In A. Pitkänen, P. A. Schwartzkroin, & S. L. Moshé (Eds.), *Models of seizures and epilepsy* (pp. 601–611). Burlington: Academic Press, http://dx.doi.org/10.1016/B978-012088554-1/50050-5, URL: http://www.sciencedirect.com/science/article/pii/B9780120885541500505.

Velíšková, J., & Velíšek, L. (2017). In A. Pitkänen, P. S. Buckmaster, A. S. Galanopoulou, & S. L. Moshé (Eds.), *Chapter 9 - Behavioral characterization and scoring of seizures in rodents* (2nd ed.). URL: http://www.sciencedirect.com/science/article/pii/B9780128040669000092.

Wang, L., Xue, W., Li, Y., Luo, M., Huang, J., Cui, W., et al. (2017). Automatic epileptic seizure detection in EEG signals using multi-domain feature extraction and nonlinear analysis. *Entropy*, *19*(6), 222. http://dx.doi.org/10.3390/e19060222.

Wijayanto, I., Hartanto, R., Nugroho, H. A., & Winduratna, B. (2019). Seizure type detection in epileptic EEG signal using empirical mode decomposition and support vector machine. In *2019 International seminar on intelligent technology and its applications* (pp. 314–319). http://dx.doi.org/10.1109/ISITIA.2019.8937205.

World Health Organisation (2019). *Key facts: Epilepsy*. W.H.O., Retrieved from https://www.who.int/news-room/fact-sheets/detail/epilepsy. (Accessed 9 June 2022).

Young Epilepsy (2021). Epilepsy facts and figures. Retrieved from https://www.youngepilepsy.org.uk/about-epilepsy/what-is-epilepsy. (Accessed 22 January 2021).

Yuan, Y., Xun, G., Jia, K., & Zhang, A. (2019). A multi-view deep learning framework for EEG seizure detection. *IEEE Journal of Biomedical and Health Informatics*, *23*(1), 83–94. http://dx.doi.org/10.1109/JBHI.2018.2871678.

Zhang, Y., Guo, Y., Yang, P., Chen, W., & Lo, B. (2019). Epilepsy seizure prediction on EEG using common spatial pattern and convolutional neural network. *IEEE Journal of Biomedical and Health Informatics*, *24*(2), 465–474. http://dx.doi.org/10.1109/JBHI.2019.2933046.

Zhang, S., Liu, G., Xiao, R., Cui, W., Cai, J., Hu, X., et al. (2022). A combination of statistical parameters for epileptic seizure detection and classification using VMD and NLTWSVM. *Biocybernetics and Biomedical Engineering*, *42*(1), 258–272. http://dx.doi.org/10.1016/j.bbe.2022.02.004.

Zhou, M., Tian, C., Cao, R., Wang, B., Niu, Y., Hu, T., et al. (2018). Epileptic seizure detection based on EEG signals and CNN. *Frontiers in Neuroinformatics*, *12*, 95. http://dx.doi.org/10.3389/fninf.2018.00095.