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ORIGINAL ARTICLE

A machine learning system for automated whole-brain seizure detection

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Abstract Epilepsy is a chronic neurological condition that affects approximately 70 million people worldwide. Characterised by sudden bursts of excess electricity in the brain, manifesting as seizures, epilepsy is still not well understood when compared with other neurological disorders. Seizures often happen unexpectedly and attempting to predict them has been a research topic for the last 30 years. Electroencephalograms have been integral to these studies, as the recordings that they produce can capture the brain's electrical signals. The diagnosis of epilepsy is usually made by a neurologist, but can be difficult to make in the early stages. Supporting para-clinical evidence obtained from magnetic resonance imaging and electroencephalography may enable clinicians to make a diagnosis of epilepsy and instigate treatment earlier. However, electroencephalogram capture and interpretation is time consuming and can be expensive due to the need for trained specialists to perform the interpretation. Automated

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detection of correlates of seizure activity generalised across different regions of the brain and across multiple subjects may be a solution. This paper explores this idea further and presents a supervised machine learning approach that classifies *seizure* and *non-seizure* records using an open dataset containing 342 records (171 *seizures* and 171 *non-seizures*). Our approach posits a new method for generalising seizure detection across different subjects without prior knowledge about the focal point of seizures. Our results show an improvement on existing studies with 88% for *sensitivity*, 88% for *specificity* and 93% for the area under the curve, with a 12% global error, using the *k-NN* classifier.

1. Introduction

Epilepsy is a chronic condition of the brain, and causes repeated seizures, commonly referred to as fits. Epilepsy is said to affect 70 million people worldwide [19]. The risk of developing epilepsy is greatest at the extremes of life with incidences more common in the elderly than the young [18] and is the cause of premature mortality for those suffering with the condition [19].

Seizures can be focal (partial) and exist in one part of the brain only, or they can be general and affect both halves of the brain. During a focal seizure, the person may be conscious and unaware that a seizure is taking place, or they may have uncontrollable movements or unusual feelings and sensations. A diagnosis of epilepsy is made with the help of an electroencephalogram (EEG). *EEG* recordings are commonly visualised as charts of electrical energy produced by the brain and plotted against time [16].

The majority of previous works on seizure detection and prediction have focused on patient-specific predictors, where a classifier is trained on one person and tested on the same person [13,10,25,26,63,9]. In this paper, the emphasis is on using EEG classification to generalise detection across all regions of the brain using multiple subject records.

A whole-brain seizure detection approach supports para-clinical evidence obtained from magnetic resonance imaging and EEG to make a diagnosis of epilepsy and instigate treatment earlier. It helps to mitigate the difficulties associated with the capture and interpretation of electroencephalogram by neurologists. In this paper, a robust data processing methodology is adopted and several classifiers are trained and evaluated, using 342 EEG segments extracted from the EEG records of 24 patients suffering with epilepsy.

The structure, of the remainder, of this paper is as follows. Section 2 describes the underlying principles of EEG and the type of features extracted from EEG signals. Section 3 discusses machine learning and its use in *seizure* and *non-seizure* classification, while Section 4 describes the evaluation. The results are discussed in Section 5 before the paper is concluded in Section 6.

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2. Seizure detection and classification

Gotman is one of the pioneers of seizure detection whose research in the area dates back to 1979. In Gotman et al. [22], he proposed a system for automatic recognition of inter-ictal epileptic activity in prolonged EEG recordings using a spike and sharp wave recognition method. Extensions to this work are presented in Koffler and Gotman [29], Gotman [21], Gotman [23], Qu and Gotman [51], while recent works have focussed on the use of functional magnetic resonance imaging (fMRI) and the correlation between cerebral hemodynamic changes and epileptic seizure events visible in EEG [36]. More recently, he has looked at automatic seizure detection in sEEG using high frequency activities in the wavelet domain [10].

In other studies, the most common classifier used to distinguish between *seizure* and *non-seizure* events has been the support vector machine (SVM). Using the CHB-MIT database and a patient-specific prediction methodology, the study in Shoeb [55] used a SVM classifier on EEG recordings from 24 subjects. The results show that a classification accuracy of 96% for *sensitivity* was produced, with a false-positive rate of 0.08 per hour. In a similar study five records from the CHB-MIT dataset (containing 65 *seizures*) were evaluated using a linear discriminant analysis classifier [28]. The overall accuracy reported was 91.8%, 83.6% for *sensitivity*, and 100% for *specificity*. For similar SVM studies using other datasets the reader is referred to [55,28,44,62].

Acharya et al. focused on using entropies for EEG *seizure* detection and seven different classifiers [6]. The best-performing classifier was the Fuzzy Sugeno classifier, which achieved 99.4% for *sensitivity*, 100% for *specificity*, and 98.1% for overall accuracy. The worst performing classifier was the Naïve Bayes Classifier, which achieved 94.4% for *sensitivity*, 97.8% for *specificity*, and 88.1% for accuracy. Nasehi and Pourghassem [43] used the same CHB-MIT dataset with a Particle Swarm Optimisation Neural Network (PSONN) which produced 98% for *sensitivity* and a false-positive rate of 0.125 per hour. Using the FRE[1] dataset Yuan et al. presented a patient-specific *seizure* detection system and an extreme machine-learning algorithm to train a neural network [65]. Twenty-one seizure records were used to train the classifier and 65 for testing. The results show that the system achieved an average of 91.92% for *sensitivity*, 94.89% for *specificity* and 94.9% for overall accuracy.

Patel et al. [49] proposed a low power, real-time classification algorithm, for detecting seizures in ambulatory EEG. The study compared linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), Mahalanobis discriminant analysis (MDA), and SVM classifiers on 13 subjects from the FRE dataset. The results show that the LDA gave the best results when trained and tested on a single patient, with 94.2% for *sensitivity*, 77.9% for *specificity*, and 87.7% for overall accuracy. When generalised across all subjects, the results show 90.9% for *sensitivity*, 59.5% for *specificity*, and 76.5% for overall accuracy.

[1] https://epilepsy.uni-freiburg.de/.

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3. Electroencephalography and feature extraction

Electroencephalography is the term given to the recording of electrical activity resulting from ionic current flows generated by neurons in the brain and is mainly used to evaluate seizures and epilepsy. In order to retrieve EEG signals, electrodes are placed on the scalp where odd numbered electrodes are placed on the left side of the scalp and even numbered electrodes on the right. Electrode locations and names are specified by the International 10–20 system [55].

The collection of raw EEG signals is always temporal. However, for analysis and feature extraction purposes, translation, into other domains, is possible and often required. These include frequency representations, via *Fourier Transform* [42,37,24,12] and wavelet transform [12,32,40,17,14,39]. The advantage of frequency-related parameters is that they are less susceptible to signal quality variations, due to electrode placement or the physical characteristics of subjects [38].

In order to obtain frequency parameters, several studies have used Power Spectral Density (*PSD*). Within PSD, *Peak Frequency* is one of the features considered in many studies. It describes the frequency of the highest peak in the *PSD*. During a seizure, EEG signals tend to contain a major cyclic component, which shows itself as a dominant peak in the *frequency domain*. In one example, Aarabi et al. used *Peak Frequency*, along with *sample entropy* and other amplitude features, to detect epileptic seizures and achieved a *sensitivity* of 98.7% and a false detection rate of 0.27 per hour [3].

Meanwhile, Ning and Lyu [45] found that *Median Frequency* displayed significant differences between *seizure* and *non-seizure* patients. By segmenting the EEG signal into five separate frequency bands for *delta* (δ: $0.5 \leqslant f \leqslant 4$ Hz), *theta* (θ: $4 \leqslant f \leqslant 8$ Hz), *alpha* (α: $8 \leqslant f \leqslant 12$ Hz): *beta* (β: $12 \leqslant f \leqslant 25$ Hz), and *gamma* (γ: $25 \leqslant f$), it was possible to predict 79 of 83 *seizures*, with a *sensitivity* value of 95.2%.

Root mean square (*RMS*) has also been considered a useful feature for distinguishing between *seizure* and *non-seizure* events. *RMS* measures the magnitude of the varying quantity and is a good signal strength estimator in EEG frequency bands [5]. In a study on neonatal *seizure* detection [50], 21 features for *seizure* classification were compared, which saw *RMS* achieves an overall accuracy of 77.71%. The study showed that *RMS* outperformed all the other features used.

Entropy has been used as a measure of the complexity, or uncertainty, of an *EEG* signal, where the more chaotic the signal is, the higher the *entropy*. There are two kinds of *entropy* estimators: *spectral entropies*, which use the amplitude of the power spectrum; and *signal entropies*, which use the time series directly [27]. Many authors agree that during a *seizure*, the brain activity is more predictable than during a normal, *non-seizure*, phase and this is reflected by a sudden drop in the *entropy* value [46,47,61,66].

Energy is a measure of the EEG signal strength. Rather than looking at the *energy* of the whole EEG signal, the energy distribution across frequency bands has been used in *seizure* detection [46]. The study found that *delta* and *theta* frequency bands saw a much larger distribution of energy during a seizure compared to normal EEG, whereas the *alpha*, *beta* and *gamma* frequency bands saw a lower *energy* distribution during a *seizure*. Using the *energy* distribution, per frequency band, as a feature achieved an overall accuracy of 94%.

Correlation dimension has been investigated as a correlation measure in several studies, which is a *nonlinear* univariate, widely used to measure *fractal dimension*. *Fractal dimension* measures the complexity of the EEG signal, in other words, the regularity and divergence of the signal [33,7]. In [1] correlation dimension and five other features for *seizure* prediction of focal neocortical epilepsy produced reasonably good results with 90.2% for *sensitivity* and 97% for *specificity*. However, when looking specifically at the *correlation dimension* they found the results dropped in 44.9% of *seizures* and increased in the pre-ictal phase in 44.9% of *seizures*. They also found that there were stronger dimension changes in the remote channels compared with those near the seizure onset.

In [8] *correlation dimension* and the largest *Lyapunov exponent* were studied to determine their ability to detect *seizures*. The study showed that neither measure on its own was useful for the task, but did work better, when they were used together. They also noted that *correlation dimension* was only useful when applied to the frequency sub-bands (*delta*, *theta*, *alpha*, *beta*, and *gamma*), and not on the entire 0–60 Hz frequency spectrum that was used in the study. The authors concluded that changes in dynamics are not spread out across the entire spectrum, but are limited to certain frequency bands.

Skewness is a third-order statistical moment, and *kurtosis* is the fourth. Along with the first and second order moments, *mean* and *variance*, respectively, the four statistical moments provide information on the amplitude distribution of a *time series*. Specifically, *skewness* and *kurtosis* give an indication of the shape of the distribution [4]. Khan et al. use *skewness* and *kurtosis*, along with normalised coefficient of variation, for *seizure* detection in paediatric patients. They managed to detect all 55 seizures from a subset of 10 patients, achieving 100% *sensitivity*, with a false detection rate of 1.1 per hour.

4. Automated whole-brain seizure detection

The aim of most studies, in EEG detection, has been to detect patient-specific focal *seizures*, rather than predicting general *seizures* across a much bigger population. As Shoeb [55] explains, a *seizure* EEG pattern is specific to a particular patient. The main reason for this is that focal seizures can occur in any part of the brain, and therefore, can only be detected in the EEG on specific channels. A classifier trained on a patient who experiences focal *seizures* in the occipital lobes, for example, would no doubt be trained on features from channels, including electrodes *O1*, and *O2* (electrodes to monitor electrical activity in the occipital lobe), as these would be the channels from the area of the *seizure* and therefore, best at detecting the *seizure*.

For this reason, and due to the configuration of the dataset, this study focuses on discriminating between *seizure* and *non-seizure* EEGs across a group of 24 subjects. The classifiers are trained on all patient records and therefore, classification is generalised across all subjects using features from channels that capture the EEG in all parts of the brain.

The approach utilises machine learning algorithms embedded in-line with existing clinical systems to enhance clinical practices in epilepsy diagnostics. The proposed algorithms support para-clinical evidence obtained from magnetic resonance imaging and electroencephalography to alleviate the capture and interpretation of electroencephalogram and help reduce costs, by minimising the need for trained specialists to perform the interpretation. The approach provides automated detection of correlates of seizure activity generalised across different regions of the brain and across multiple subjects.

4.1. Methodology

The *CHB-MIT* dataset is a publicly available database from physionet.org that contains 686 scalp EEG recordings from 23 patients treated at the Children's Hospital in Boston. The subjects had anti-seizure medication withdrawn, and EEG recordings were taken for up to several days after.

The EEG recordings are divided among 24 cases (one patient has two sets of EEG recordings 1.5 years apart). The patients range between 1.5 and 22 years of age, and there are 5 males and 17 females. Case 24 was added after the original dataset was collected and has no patient data.

Most of the recordings are one hour long, although those belonging to case 10 are two hours and those belonging to cases 4, 6, 7, 9, and 23 are four hours long. Records that contain at least one seizure are classed as *seizure* records and those that contain no seizures as *non-seizure* records. Of the 686 records, 198 contain seizures.

Although the description supplied with the dataset states that recordings were captured using the international 10–20 system of EEG electrode positions and nomenclature, it was found that 17 of the files that contained *seizures* had different channel montages to the rest of the seizure files. Therefore, these 17 records have been excluded from this study, leaving 181 seizure files. A further 10 records were removed from the dataset due to a large number of missing data.

The final dataset used in this study was constructed from 60-s data blocks (mean ictal length across the 171 seizure records), comprising the ictal data (*seizure*), which were extracted from 171 *seizure* files. Table 1 provides a summary of the ictal data with the 171 ictal blocks.

The results show that 25% of the data blocks (42.75 blocks) contain less than or equal to 23 s of ictal data, which means that 75% of our data blocks (128.25

blocks) contain 23 s or more of ictal data, with the average block containing 45 s if we consider the median. However, the data contain outliers, i.e. the Max value is 752. To get a more representative summary the first 60 s of ictal data is used from each seizure record that lasts longer than 60 s. Table 2 provides a summary of the data.

The average block now contains 45 s if we consider the median, 40.52% if we consider the mean. More importantly, the majority of the data blocks (64%) of the 171 ictal blocks contain 30 s or more of icta data. In a real-world scenario, it is unlikely that, whatever window size we select, data blocks will contain only ictal data. The more realistic case is that it will contain both ictal and non-ictal data. By having 60-s blocks with different ictal and non-ictal data splits, this allows us to determine the performance of the classifiers under conditions more aligned with a real-world situation. However, future work will explore optimal window sizes. To balance the dataset, 171 data blocks randomly extracted from non-seizure files were also added to the dataset.

Fig. 1 shows the processes used in the methodology to process the data, that include filtering, feature extraction, feature selection, classification and finally validation.

Each of these processes is discussed in more detail below. Fig. 1 shows a data science methodology that produces a robust data analytics based solution.

4.1.1. Data pre-processing

In the *CHB-MIT* database, each record was sampled at 256 Hz, with 16-bit resolution. Signals were recorded simultaneously through twenty-three different channels, via 19 electrodes and a ground attached to the surface of the scalp.

A bandpass filter was applied to each of the 342 EEG segments (171 *seizures*, 171 *non-seizures*) to extract the EEG data in each of the frequency blocks. Second order butterworth filters were used as they offer good transition band characteristics at low coefficient orders; thus, they can be implemented efficiently. This results in five columns of additional data; the complete bandwidth (0.5–30 Hz), *delta* (δ: $0.5 \leqslant f \leqslant 4$ Hz), *theta* (θ: $4 \leqslant f \leqslant 8$ Hz), *alpha* (α: $8 \leqslant f \leqslant 12$ Hz): and *beta*

Table 1 Summary of ictal seizure data in all variable length ictal blocks.

Min	1st Qu.	Median	Mean	3rd Qu.	Max
2.00	23.00	45.00	61.53	73.00	752.00

Table 2 Summary of ictal seizure data in 60-s ictal blocks.

Min	1st Qu.	Median	Mean	3rd Qu.	Max
2.00	23.00	45.00	40.52	60.00	60.00

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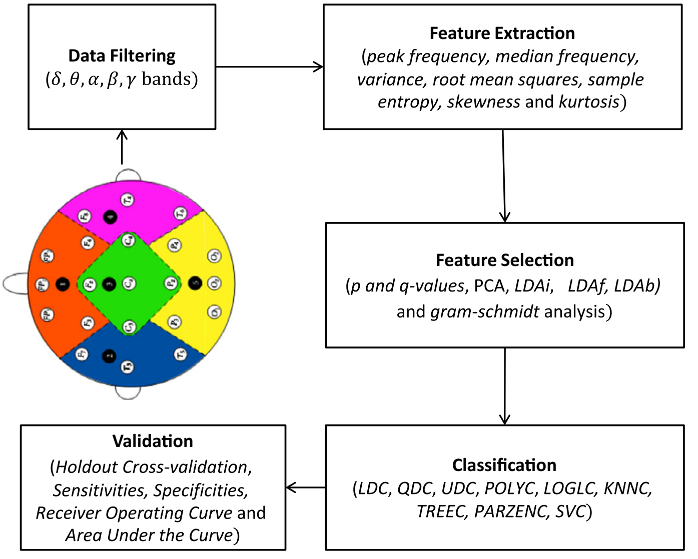

Figure 1 Methodology data processes.

(β: $12 \leqslant f \leqslant 25$ Hz). In other words, each block contains 115 columns of data for each of the 23 EEG channels in the original data (N = 23 * (complete bandwidth + delta + theta + alpha + beta) = 23 * 5 = 115).

4.1.2. Feature selection

The feature vectors in this paper are generated from the 171 *seizure* files and 171 *non-seizure* blocks, obtained from 23 patients, using *Peak Frequency*, *Median Frequency*, *variance*, *root mean squares*, *sample entropy*, *skewness* and *kurtosis*. These features were extracted from each of the 115 columns in an EEG block (N = 7 features * 115 columns = 805). The literature reports that *Median Frequency*, *sample entropy* and *root mean square* have the most potential to discriminate between *seizure* and *non-seizure* records. To validate these findings, the discriminant capabilities of each feature are determined using several measures: *statistical significance* (*p and q-values*), *principal component analysis* (*PCA*) – *Principle Component one* (*PC1*) *and Principle Component two* (*PC2*), *linear discriminant analysis independent search* (*LDAi*), *linear discriminant analysis forward search* (*LDAf*), *linear discriminant analysis backward search* (*LDAb*) and *gram-schmidt* (*GS*) analysis.

Using these measures, the top 20 uncorrelated features were extracted from all regions of the EEG scalp readings (region-by-region feature extraction is considered later in the paper). For example, in the case of *p-values* we select the top 20 uncorrelated features (from the 805 features that we have) that have the highest *p-values* and use these features with all our classifiers. The *tttest2* function in Matlab can be used to extract *p-values* and they can be ranked using the *sort* function.

These features are then used to determine which classifier performs the best. The same approach is used for the *q-values*. The *mafdr* function in Matlab can be used to determine the *q-values* and again, they can be ranked using the *sort* function. In the case of Principle Component one (*PC1*), the top 20 uncorrelated features that comprise the most variance in *PC1* were selected and evaluated against all classifiers. The same approach was used for *PC2*. In the case of linear discriminant analysis feature selection, the *featseli*, *featself*, and *featselb* provided by the Matlab pattern recognition toolbox PRTools is used to provide an ordered ranking of features. In a similar way, the Gram-Schmidt ranks and orders each feature by importance.

Table 3 shows that the best results were obtained from the *linear discriminant analysis backward search* technique with an area under the curve (*AUC*) of 91%. This was followed closely by statistical *p* and *q-values* with *AUC* values of 90% and 89% respectively.

Fig. 2 shows (using PCA) that several RMS and *Median Frequency* features, from different channels and frequency bands, appear along the principal component. This is consistent with the findings in Ning and Lyu [45], Abdul-latif et al. [5], Paivinen et al. [47]. The vertical axis shows that CH12_48_Var, CH9_48_Var, and CH3_0530_MFreq features align closest with the second principal component. Again, these results are consistent with the findings in Ning and Lyu [45], Abdul-latif et al. [5], Paivinen et al. [47].

This study also extracts the top five uncorrelated features from each of the five regions covered by the *EEG* scalp electrodes as shown in Table 4. This ensures that each region is represented without the bias from all other regions, and allows classifiers to detect focal seizures in different parts of the brain. The features extracted, using the generalised and region-by-region approach, are used to evaluate the capabilities of several classifiers considered in this study and are the top five features per region selected based on their rank determined by the linear discriminant backward search technique, creating five feature sets containing five features each. The top 20 uncorrelated features and the 25 region-by-region features are compared in the evaluation.

Table 3 Results for feature selection techniques.

knnc *p*	knnc *q*	svn *PC1*	knnc *PC2*	tree *PC1 & 2*	knnc *LDAi*	loglc *LDAf*	knnc *LDAb*	loglc *GS*
AUCs for feature selection techniques								
90	89	83	88	87	86	88	91	88
Sensitivities for feature selection techniques								
83	84	53	86	80	78	76	84	76
Specificities for feature selection techniques								
83	82	90	81	79	80	85	85	86

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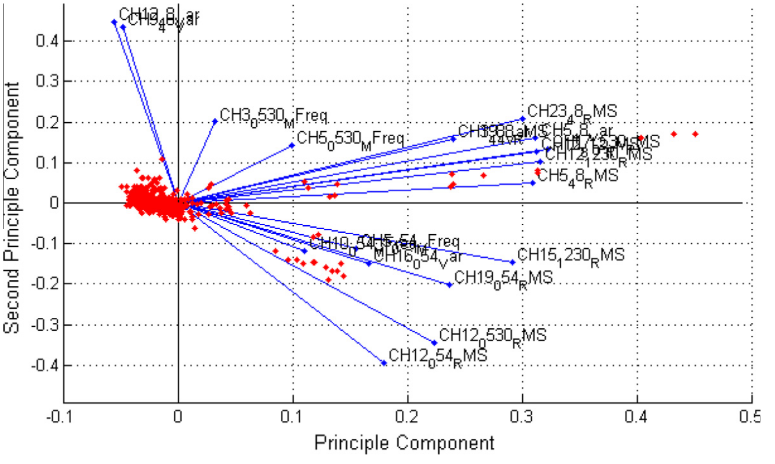

Figure 2 *PCA* for *Median Frequency* and *RMS* feature discrimination.

4.1.3. Classification

Following an analysis of the literature, the study in this paper adopts simple, yet powerful algorithms. These include the *linear discriminant classifier* (*LDC*), *quadratic discriminant classifier* (*QDC*), *uncorrelated normal density based classifier* (*UDC*), *polynomial classifier* (*POLYC*), *logistic classifier* (*LOGLC*), *k-nearest neighbour* (*KNNC*), *decision tree* (*TREEC*), *parzen classifier* (*PARZENC*) and the *support vector machine* (*SVC*) [61].

4.1.4. Validation methods

In order to determine the overall accuracy of each of the classifiers several validation techniques have been considered. These include *Holdout Cross-Validation*, *Sensitivities*, *Specificities*, *Receiver Operating Curve* (*ROC*) and *area under the curve* (*AUC*). The Holdout Cross-Validation technique uses 80 per cent of randomly selected observations ($N = 19.2$) to train the algorithms and 20 per cent of randomly selected test cases to test the algorithms ($N = 3.8$).

5. Evaluation

5.1. Results using top twenty uncorrelated features ranked using LDA backward search feature selection

In the first evaluation, the top twenty uncorrelated features, extracted from each of the frequency bands within each of the EEG channels, and nine classifiers are used. The performance for each classifier is evaluated using the *sensitivity*, *specificity*, *mean error*, *standard deviation* and *AUC* values with 100 simulations and randomly selected training and testing sets for each simulation. In this study,

Table 4 Top five features for the five scalp regions.

Feature set	Description	Features
1	Top 5 features from region 1	RMS CH2 0.5–30 Hz Samp entropy CH2 0.5–4 Hz RMS CH2 4–8 Hz RMS CH2 0.5–4 Hz Samp entropy CH1 0.5–4 Hz
2	Top 5 features from region 2	RMS CH16 0.5–30 Hz RMS CH16 0.5–4 Hz RMS CH12 12–30 Hz RMS CH16 12–30 Hz RMS CH16 4–8 Hz
3	Top 5 features from region 3	RMS CH3 0.5–30 Hz RMS CH3 0.5–4 Hz RMS CH4 4–8 Hz Med Freq CH3 0.5–4 Hz RMS CH4 0.5–30 Hz
4	Top 5 features from region 4	RMS CH18 4–8 Hz RMS CH18 0.5–30 Hz RMS CH17 0.5–30 Hz RMS CH17 0.5–4 Hz RMS CH18 0.5–4 Hz
5	Top 5 features from region 5	RMS CH21 0.5–30 Hz RMS CH21 4–8 Hz RMS CH21 12–30 Hz RMS CH21 8–12 Hz RMS CH21 0.5–4 Hz

high *sensitivities* are important to ensure that seizures can be detected within an alarm system. High *specificities* are considered equally important as high false alarm rates (more than 1 per hour) will deter doctors from using it.

5.1.1. Classifier performance

The first evaluation uses all the *seizure* and *non-seizure* blocks from all subjects in the *CHB-MIT* dataset (171 *seizures* and 171 *non-seizures*). The simulations use 80% for training and 20% for testing. Table 5, shows the mean averages obtained over 100 simulations for the *sensitivity*, *specificity*, and *AUC*.

As shown in Table 5, the *sensitivities* (*seizure*), in this initial test, are low for all classifiers. This is interesting given that the dataset is balanced between *seizure* and *non-seizure* blocks. One possible reason for this is that the *ictal* length across the 171 records was 60 s. However, in the *CHB-MIT* records *ictal* periods ranged between 2 and 752 (cut down to 60 s) seconds. It is possible that some *ictal* blocks resemble *non-seizure* records resulting in misclassification (particularly blocks that contain 2 s of *ictal* data). However, given that 64% of the ictal blocks contain more than 30 s of icta data, this is appropriate for training. Furthermore, it is a decision that is supported by the relatively high *sensitivity*, *specificity* and AUC

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Table 5 Classifier performance results for top 20 uncorrelated features.

Classifier	Sensitivity (%)	Specificity (%)	AUC (%)
LDC	70	83	54
QDC	65	92	62
UDC	39	95	65
POLYC	70	83	83
LOGLC	79	86	89
KNNC	84	85	91
TREEC	78	80	86
PARZENC	61	86	54
SVC	79	86	88

values. Nonetheless, further investigation is required. Table 6 shows the error and standard deviations obtained over 100 iterations.

The results show that all techniques are able to achieve a classification error, lower than the base-rate error of 50% (i.e. 171/342).

5.1.2. Model selection

The receiver operator characteristic (*ROC*) curve shows the cut-off values for the false negative and false-positive rates. Fig. 3 indicates that several of the classifiers performed reasonably well. The *AUC* values in Table 4 support these findings with good accuracy values for the *LOGLC* and *KNNC* classifiers.

5.2. Results using top five uncorrelated features ranked using lda backward search feature selection from five head regions

In the second evaluation, the top five uncorrelated features, extracted from five main regions across the head, are used to determine whether the detection of *seizures* can be improved. Again, the performance for each classifier is evaluated using the *sensitivity*, *specificity*, *mean error*, *standard deviation* and *AUC* values with 100 simulations and randomly selected training and testing sets for each simulation.

Table 6 Cross validation results for top 20 uncorrelated features.

Classifier	80% Holdout: 100 repetitions	
	Err	*SD*
LDC	0.23	0.05
QDC	0.21	0.04
UDC	0.32	0.04
POLYC	0.23	0.05
LOGLC	0.17	0.04
KNNC	0.15	0.04
TREEC	0.20	0.05
PARZENC	0.26	0.04
SVC	0.17	0.04

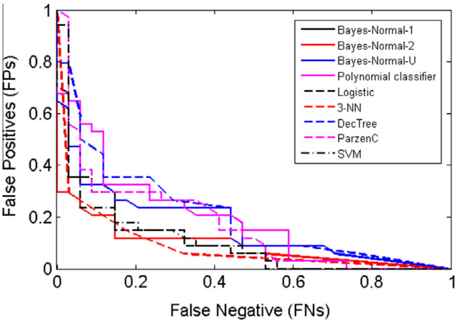

Figure 3 Received operator curve for top 20 uncorrelated features.

5.2.1. Classifier performance

The simulations use 80% for training and 20% for testing. As shown in Table 7, the *sensitivities* (*seizure*), for most of the algorithms have improved, including the *specificities* values. The *AUC* results also show improvements for several of the classifiers, with 93% achieved by the *KNNC* classifier. From the previous results, we find a 4% increase in *sensitivities*, a 3% increase in *specificities* and a 2% increase in the performance of the *KNNC* classifier, with other classifiers improving by similar values.

Again, the results in Table 8 show that the *mean error* has decreased by 3% using the *holdout* technique. This indicates that using a region-by-region approach is better at discriminating between *seizure* and *non-seizure* events.

Overall, the *mean errors* produced, using all of the validation techniques, are significantly lower than the expected error, which is 171/342, i.e. 50%.

5.2.2. Model selection

Again, the *ROC* curve shows the cut-off values for the false-negative and false-positive rates. Fig. 4 indicates that the performance of several classifiers improved. The *AUC* values in Table 7 support these findings with the *KNNC* classifier showing a 2% increase in performance.

Table 7 Classifier performance results from top five uncorrelated features from five head regions.

Classifier	Sensitivity (%)	Specificity (%)	AUC (%)
LDC	78	88	55
QDC	84	86	60
UDC	51	91	70
POLYC	78	88	89
LOGLC	82	84	90
KNNC	88	88	93
TREEC	82	81	89
PARZENC	81	93	61
SVC	85	86	90

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Table 8 Cross validation results from top five uncorrelated features from five regions.

Classifier	80% Holdout: 100 repetitions	
	Err	*SD*
LDC	0.16	0.04
QDC	0.14	0.04
UDC	0.29	0.04
POLYC	0.16	0.04
LOGLC	0.17	0.04
KNNC	0.12	0.03
TREEC	0.18	0.05
PARZENC	0.13	0.04
SVC	0.14	0.03

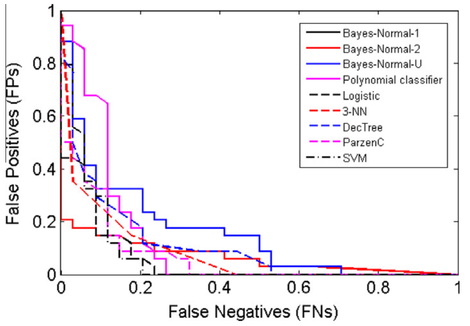

Figure 4 Received operator curve for top five uncorrelated features from five head regions.

6. Discussion

The study has focused on discriminating between *seizure* and *non-seizure* EEG records across a group of 23 subjects, rather than a single individual. The classifiers are trained using all 24 cases, and therefore, classification is generalised across the whole population contained in the CHB-MIT database. To achieve this, features from all the channels that capture the EEG in all parts of the brain were used. In the initial classification results, the top 20 uncorrelated features from the whole of the head (not region-by-region) were extracted from 805 possible features. This was determined using the *linear discriminant analysis backward search* technique to rank features. This approach achieved reasonably good results, using the *KNNC* classifier, with 84% for *sensitivity*, 85% for *specificity*, 91% for the *AUC*, with a global error of 15%.

Interestingly, the features used in this initial evaluation, involved channels from the four lobes of the brain, *occipital*, *parietal*, *frontal*, and *temporal*, but not the channels spread across the centre of the head. This implied that rather than having generalised seizures across the whole of the brain, a majority of focal seizures occurred in each of the lobes. Unlike studies that used the BONN dataset, which only contains one channel, or the FRE dataset, that contains six channels and

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identifies focal and extra focal channels, the CHB-MIT database used in this study contains 23 channels with no information on the seizure type or location.

Using the top five uncorrelated features from EEG channels specific to the five main regions of the head improved the *sensitivities* and *specificities*, while producing high AUC values. The best classification algorithm was again the KNNC classifier, which achieved 88% for *sensitivity*, 88% for *specificity*, and an AUC value of 93% with a 12% global error. This was followed closely by the SVC classifier, which achieved 85% for sensitivity, 86% for specificity, and an AUC value of 90% with a 14% global error.

Comparing our results with other studies, we find that Shoeb [55] produced a better sensitivity value (96%) than those reported in this study. However, their approach utilised a SVM classifier trained and tested on an individual patient and was not concerned with the generalisation of seizures across a bigger population group. Consequently, the 88% sensitivity value produced in this paper appears to be extremely good given that our classifiers were trained and tested on data from 23 different patients, not just one. In a similar study, Nasehi and Pourghassem [43] used a neural network and reported a *sensitivity* value of 98%, which again is higher than the results reported in this study. However, as with the work of Shoeb, the classifiers were trained and tested on specific patients.

In comparison with other studies that adopted a similar approach to our study, our approach produced better overall results. For instance, Khan et al. [28] report a 83.6% *specificity* value, while Patel et al. [49] report 94% for *sensitivity*, 77.9% for *specificity*, and 87.7% for overall accuracy. Yuan et al. [66] report 91.72% for *sensitivity*, 94.89% for *specificity*, and 94.9% for accuracy, while Aarabi et al. [2], Kannathal et al. [27], report similar results. The results found in this paper can be compared in more detail with the papers listed in Table 9.

This work has potential future clinical applications in the investigation of patients with suspected *seizure* disorders and may be useful in the assessment of patients with non-epileptic attack disorder (NEAD). Introducing automated seizure detection technologies could help increase capacity within healthcare systems such as the UKs National Health Service (NHS), which currently suffers from a chronic shortage of trained clinical neurophysiologists to interpret EEGs. Tele-EEG reporting has previously been suggested as a solution and more recently online systems [20,41], which are interesting approaches, but carry increased costs and concerns over data security. Nonetheless, these, including automated seizure detection may be viable solutions, following further work aimed at improving accuracy further.

7. Conclusions and future work

Within a supervised-learning paradigm, this study has addressed this challenge by utilising EEG signals to classify seizure and non-seizure records. Our approach posits a new method for generalising seizure detection across different subjects

Table 9 Seizure detection studies and classification results.

Author	Year	Data set	Classifier	Patients	Sens (%)	Spec (%)	Acc (%)	FPR (h)
Aarabi et al. [2]	2006	AMI	BPNN	6	91.00	95.00	93.00	1.17
Acharya et al. [6]	2012	BONN	PNN, SVM, C4.5, BC, FSC, KNN, GMM	10	94.4–99.4	91.1–100	88.1–95.9	–
Bao et al. [11]	2008	BONN	PNN	10	–	–	71–96.8	–
Chandaka et al. [15]	2009	BONN	SVM	10	92.00	100	95.96	–
Kannathal et al. [27]	2005	BONN	ANFIS	10	91.49	93.02	92.2	–
Kumar et al. [30]	2010	BONN	EN, RBNN	10	–	–	94.5	–
Kumari and Jose [31]	2011	BONN	SVM	5	100.00	100	100	0
Nicalaou and Georgiou [44]	2012	BONN	SVM	10	94.38	93.23	80.9–86.1	–
Song and Lio [56]	2010	BONN	BPNN, ELM	10	97.26	98.77	95.67	–
Subasi [59]	2007	BONN	MPNN, ME	10	95.00	94	94.5	–
Subasi and Gursoy [60]	2010	BONN	SVM		99–100	98.5–100	98.75–100	–
Yuan et al. [64]	2011	BONN	SVM, BPNN, ELM	10	92.50	96	96	–
Zheng et al. [67]	2012	BXH	SVM	7	44.23	–	–	1.6–10.9
Khan et al. [28]	2012	CHBMIT	LDA	5	83.60	100	91.8	
Nasehi and Pourghassem [43]	2013	CHBMIT	IPSONN	23	98.00	–	–	0.125
Shoeb [55]	2009	CHBMIT	SVM	24	96.00	–	–	0.08
Rasekhi et al. [52]	2013	EUR	SVM	10	73.90	–	–	0.15
Park et al. [48]	2011	FRE	SVM	18	92.5–97.5	–	–	0.2–0.29
Patel et al. [49]	2009	FRE	SVM, LDA, QDA, MDA	21	90.9–94.2	59.5–77.9	76.5–87.7	–
Williamson et al. [62]	2011	FRE	SVM	21	90.80	–	–	0.094
Yuan et al. [66]	2012	FRE	ELM	21	93.85	94.89	94.9	0.35
Bao et al. [11]	2009	JPH	PNN	12	–	–	94.07	–
Sorensen et al. [57]	2010	RIG	SVM	6	77.8–100	–	–	0.16–5.31
Seng et al. [54]	2011	SGR & BONN	PNN, SVM	21 + 10	–	–	99.9	–
Subasi [58]	2006	Unknown	DFNN	5	93.10	92.8	93.1	–

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without prior knowledge about the focal point of seizures. Our results show an improvement on existing studies with 88% for sensitivity, 88% for specificity and 93% for the area under the curve, with a 12% global error, using the k-NN classifier.

The results suggest that the algorithms in-situ with existing clinical systems and practices may enable clinicians to make a diagnosis of epilepsy and instigate treatment earlier. It can help to reduce costs by limiting the number of trained specialists required to perform the interpretation by automating the detection of correlates of seizure activity generalised across different regions of the brain and across multiple subjects.

There are a large number of features reported in the literature, which have not been considered in this paper. In particular our future work will consider the set of features described in Logesparan et al. [34], Logesparan et al. [35]. Furthermore, our future work will investigate the use of more advanced machine learning algorithms, despite the good performance of the classifiers considered in this paper. In particular, we will investigate the use of convolutional neural networks [53] and SVM with different kernels [54].

Window sizes will also be considered to determine whether further improvements on accuracies can be made. Future development will also utilise regression analysis and a larger number of observations. This may help to define the characteristics of the pre-ictal phase. In addition, more advanced classification algorithms, and techniques, will be considered, including advanced artificial neural network architectures (higher order and spiking neural networks). The investigation and comparison, of features, such as fractal dimension and cepstrum analysis, autocorrelation zero crossing and correlation dimension, have also not been performed. These techniques should be investigated in a head-to-head comparison, with linear methods.

The paper has investigated the use of classic yet powerful machine learning algorithms and evaluated their ability to detect correlates of seizure activity. While the results are convincing the paper does not address how the system can be generalised for normal use. Furthermore, it does not address real-time concerns where performance will degraded significantly. The approach evaluates the algorithms using offline data; however, this is not a good indicator of the system's ability as the signals that are used to train and test the algorithms are processed and cleaned and appropriate features extracted. This is a major concern and our future work will look to implement the methodology pipeline using real-time signals, using advances in the Internet of Things and Big Data community that currently utilise data processing technologies, such as Apache Spark.

Finally, there are concerns regarding the verification of the results produced using the CHB-MIT dataset against other datasets. Our future work will investigate the use of a bigger dataset, using patients provided by our co-author from The Walton Centre NHS Foundation Trust, and other datasets that permit access to verify the findings in this paper.

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Overall, the study demonstrates that classification algorithms provide an interesting line of enquiry, when separating seizure and non-seizure records.

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