**O****bjective evaluation metrics for automatic classification of EEG events**

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**Abstract:** The evaluation of machine learning algorithms in biomedical fields for applications involving sequential data lacks standardization. Common quantitative scalar evaluation metrics such as sensitivity and specificity can often be misleading depending on the requirements of the application. Evaluation metrics must ultimately reflect the needs of users yet be sufficiently sensitive to guide algorithm development. Feedback from critical care clinicians who use automated event detection software in clinical applications has been overwhelmingly emphatic that a low false alarm rate, typically measured in units of the number of errors per 24 hours, is the single most important criterion for user acceptance. Though using a single metric is not often as insightful as examining performance over a range of operating conditions, there is a need for a single scalar figure of merit. In this paper, we discuss the deficiencies of existing metrics for a seizure detection task and propose several new metrics that offer a more balanced view of performance. We demonstrate these metrics on a seizure detection task based on the TUH EEG Corpus. We show that two promising metrics are a measure based on a concept borrowed from the spoken term detection literature, Actual Term-Weighted Value, and a new metric, Time-Aligned Event Scoring (TAES), that accounts for the temporal alignment of the hypothesis to the reference annotation. We demonstrate that state of the art technology based on deep learning, though impressive in its performance, still needs significant improvement before it will meet very strict user acceptance guidelines.

**Keywords:** electroencephalograms, EEG, machine learning, evaluation metrics

# Introduction

Electroencephalograms (EEGs) are the primary means by which physicians diagnose and manage brain-related illnesses such as epilepsy, seizures and sleep disorders . Automatic interpretation of EEGs has been extensively studied in the past decade -. However, even though many research systems report impressive levels of accuracy in research publications, widespread adoption of commercial technology has yet to happen in clinical settings primarily due to the high false alarm rates of these systems . In this paper, we investigate the gap in performance between research and commercial technology and discuss how these perceptions are influenced by a lack of standardized scoring methodologies.

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There are in general two types of ways to evaluate machine learning technology: user acceptance testing  and objective performance metrics based on annotated reference data . User acceptance testing is time-consuming and expensive. It has never been a practical way to guide technology development because algorithm developers need rapid turnaround times on evaluations. Hence evaluations using objective performance metrics, such as sensitivity and specificity, are common in the machine learning field . With this approach, it is very important to have a rich evaluation dataset and a performance metric that correlates well with user and application needs. The metric must have a certain level of granularity so that small differences in algorithms can be investigated and parameter optimizations can be evaluated. For example, in speech recognition applications, word error rate has been used for many years because it correlates well with user acceptance testing but provides the necessary level of granularity to guide technology development. Despite many years of research focused on finding better performance metrics , word error rate remains a valid metric for technology development and assessment.

Sequential pattern recognition applications, such as speech recognition, keyword search or EEG analysis, require additional considerations. Data, typically organized in files on a computer, are not simply assessed with an overall judgment (e.g., “did a seizure occur somewhere in this file?”). Instead, the locality of the hypothesis must be considered – to what extent did the start and end times of the hypothesis match the reference transcription. This is a complex issue since a hypothesis can partially overlap with the reference annotation, and a consistent mechanism for scoring such events must be adopted. Unfortunately, there is no such standardization in the EEG literature. For example, Wilson et al. advocates using a term-based metric involving of sensitivity and specificity. Each term is created by connecting consecutive decisions of the same class. A hypothesis is counted as a true positive when it overlaps with one or more reference annotations. A false positive corresponds to an event in which a hypothesis annotation does not overlap with any of the reference annotations. Kelly et al. recommends using a metric that measures sensitivity and false alarms. A hypothesis is considered a true positive when time of detection is within two minutes of the seizure onset. Otherwise it is considered a false positive. Baldassano et al. uses an epoch-based metric that measures false positive and negative rates as well as latency. The development, evaluation and ranking of various machine learning approaches is highly dependent on the choice of a metric.

A large class of bioengineering problems, including seizure detection, involve prediction as well as classification. In prediction problems, we are often concerned with how far in advance of an event (or after the event has occurred) we can predict an outcome. Accuracy of prediction varies with latency, so this type of performance evaluation adds some complexity to the process. Winterhalder et al. have studied this problem extensively and argue for a scoring based on long-term considerations. In this paper, we are not concerned with these types of prediction problems. We are focused mainly on assessing the accuracy of classification and assessing the proximity of these classifications to the actual event.

Therefore, in this paper, we analyze several popular scoring metrics and discuss their strengths and weaknesses on sequential decoding problems. We introduce several alternatives, such as the Actual Term-Weighted Value that have proven successful in other fields, and discuss their relevance to EEG applications. We present a comparison of performance for several systems using these metrics and discuss how this correlates with overall user acceptance.

# Method

Researchers in biomedical fields typically report performance in terms of sensitivity and specificity . In a two-class classification problem, such as seizure detection, we can define four types of errors:

True Positives (TP): the number of ‘positives’ detected correctly

True Negatives (TN): the number of ‘negatives’ detected correctly

False Positives (FP): the number of ‘negatives’ detected as ‘positives’

False Negatives (FN): the number of ‘positives’ detected as ‘negatives’

Sensitivity (TP/(TP+FN)) and specificity (TN/(TN+FP)) are derived from these quantities. There are a large number of auxiliary measures that can be calculated from these four basic quantities and are used extensively in the literature. These are summarized concisely in . For example, in information retrieval problems, systems are often evaluated using precision (TP/(TP+FP)), recall (another term for sensitivity) and F1 score (2•TP/(2•TP+FP+FN)). However, none of these measures address the time scale on which the scoring must occur, which is critical in the interpretation of these measures.

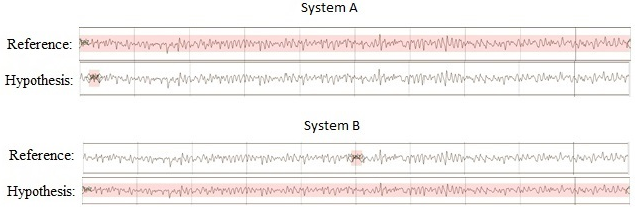
In some applications, it is preferable to score every unit of time. With multichannel signals, such as EEGs, scoring for each channel each unit of time might be appropriate. However, it is more common in the literature to simply score a summary decision per unit of time that is based on the per-channel inputs (e.g., a majority vote). We refer to this type of scoring as epoch-based . An alternative, that is more common in speech and image recognition applications, is term-based , in which we consider the start and stop time of the event, and each event identified in the reference annotation is counted once. There are fundamental differences between the two conventions. For example, one event containing many epochs will count more heavily in an epoch-based scoring scenario. Epoch-based scoring generally weights duration of events more heavily.

Time-aligned scoring is essential to sequential decoding problems. But to implement such scoring in a meaningful way, there needs to be universal agreement on how to assess overlap between the reference and the hypothesis. For example, demonstrates a typical issue in scoring. The machine learning system correctly detected *5* seconds of a *10*-sec event. Essentially *50%* of the event is correctly detected, but how that is reflected in the scoring depends on the specific metric. Epoch-based scoring with an epoch duration of *1* sec would count *5* FN errors and *5* TP errors. Term-based scoring would potentially count this as a correct recognition depending on the way overlaps are scored.



**Figure 1.** A typical situation where a hypothesis has a 50% overlap with the reference

The term-based metrics score on an event basis and do not count individual frames. A typical approach for calculating errors in term-based scoring is the Any-Overlap method [30][31]. TPs are counted when the hypothesis overlaps with reference annotation. FPs correspond to situations in which the hypothesis does not overlap with the reference. The metric ignores the duration of the term in the reference annotation. In , we demonstrate two extreme cases for which this metric fails. In each case, *90%* of the event is incorrectly scored. In the first case, system A does not detect approximately *9* seconds of a seizure event, while in the second case, system B detects incorrectly detects an additional *9* seconds of time in which the event hypothetically occurred. Any-Overlap is considered a very permissive way of scoring, resulting in artificially high sensitivities.



**Figure 2.** Detection rates for the Any-Overlap metric are 100% even though large portions of the event are missed.

<..start here...>

This paragraph talks about DET curves, ROC and AUC... The balance between sensitivity and FA rate is desired for developing a stable system and has been studied extensively in other communities focused on event-spotting technology such as Spoken Term Detection (STD) in voice signals [xx]. In this article we introduce a measure that we borrow from this research community is the Actual Term-Weighted Value (ATWV) [xx] which is based on the notion of a Detection Error Tradeoff (DET) curve [xx]. A DET curve is very similar to a Receiver Operating Characteristic (ROC) originally developed to assess the performance of a communications system [xx]. Also, the article argues that the commonly-accepted evaluation metrics does not fully meet the need of machine learning problems in the EEG research community. The deficiencies of the current evaluation measures lead us to suggest Spoken Term Detection (STD) which is used widely in speech recognition field and Time-Aligned Event Scoring **(**TAES) which counts fractional hits, miss and false alarms per event as a novel metric for biomedical applications.

Therefore, in this paper, we present results for five scoring algorithms and one derived measure:

1. *NIST Actual Term-Weighted Value* (ATWV): based on NIST’s popular scoring package (F4DE v3.3.1), this package ... one sentence summary ...;
2. *Dynamic Programming Alignment* (DPALIGN): similar to the NIST package known as SCLite, this algorithm uses dynamic programming algorithm to time align terms by ignoring the time-scale on which the events occur;
3. *Epoch-Based Sampling* (EPOCH): treats the reference and hypothesis as signals, samples each at a fixed epoch duration, and counts errors accordingly;
4. *Any-Overlap Method* (OVLP): similar to ..., but uses the any-overlap criterion to count errors;
5. *Time-Aligned Event Scoring* (TAES): similar to (4), but considers partial matches and weights errors according to the degree of match;
6. *Inter-Rater Agreement* (IRA): uses EPOCH scoring to estimate errors, and then ...

We now briefly describe each of these approaches and provide several examples that compare and contract these approaches.

## NIST Actual Term-Weighted Value (ATWV)

The first scoring method, known as NIST scoring, has been used extensively in audio spoken term detection tasks [x]...

## Dynamic Programming Alignment (DPALIGN)

xxxxx

## Epoch-Based Sampling (EPOCH)

xxxxx

## Any-Overlap Method (OVLP)

Xxx

## Time-Aligned Event Scoring (TAES)

xxx

## Inter-Rater Agreement (IRA)

The last paragraph of section 2.6 should lead into the results section.

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keyword search to Additionally, discussing one more popular metric in biomedical field called Dynamic Programming (DP) alignment metric. This metric is commonly used in DNA sequence matching to efficiently align two strings with different lengths and compute distance between them. The DP alignment method is based on minimizing the Levenshtein distance. To find the alignment with minimum score using DP, the error matrix of two sequences is computed. The error matrix E (i, j) is distance between element ith element in first sequence and jth element in second sequence [20]. The DP alignment scoring metric emphasizes on the sequence of event’s appearance with respect to the reference event. Both Any-Overlap and DP alignment metric suffer from lack of focus on temporal domain. Apart from holding few similar features, these two metrics are significantly different among themselves. One obvious difference to notice is: Any-Overlap metric considers partial overlap as a hit score whereas DP alignment only relies on the reference and hypothesis event’s sequences.

In this section, we explore the Spoken Term Detection (STD) and Time-Aligned Event Scoring **(**TAES) algorithms. The Spoken Term Detection (STD) is a speech processing task in which the goal is to find all the occurrences of a textual “keyword”, a sequence of one or more words, in a large corpus of speech data. In 2006, the U.S. National Institute of Standards and Technology (NIST) created the STD evaluation initiative to facilitate research and development of technology for retrieving information from archives of speech data. STD detects all the occurrences of each given term in the reference files. In this evaluation methodology, an estimate is required for the number of trails in the reference. If there are no discrete trials in a continuous reference, a constant will be specified as number of trials. Then, alignment between detected occurrence and reference is needed. This step is done by applying the Hungarian solution to the Bipartite Graph [27] matching problem. It uses the kernel function that numerically compares the mapping of system and reference occurrences, as well as the missed detections and false alarms. The kernel function first determines if the reference/system occurrences are mappable by requiring the system occurrence to be within a temporal tolerance collar (ΔT) of the reference occurrence. Specifically, the midpoint of the system occurrence must be within the interval from ΔT before the beginning to ΔT after the end of the reference occurrence. The performance of a system is evaluated base on detection error tradeoff (DET) curves and an Actual Term-Weighted Value (ATWV) for a specific operating point. ATWV essentially assigns an application-dependent reward to each correct detection and a penalty to each incorrect detection. The ATWV is a measure for balancing between sensitivity and FA rate. The commonly acceptable system has ATWV greater than 0.5.



**Figure 2.** The system has one True Positive (TP) and five False Positives (FPs) based on STD evaluation metric.

The STD method, just like any other metrics, has its own set of challenges including approach of calculating detection rate and number of FAs. The deficiency of the method in computing detection rate is similar to Any-Overlapped approach where both metrices ignore duration of correct term. For example, detection rates of systems which are illustrated in figure 1 and figure 2 based on STD method are 100% without any misses and FAs, so that yields a system with perfect sensitivity. Regarding the method of counting FA, consider a case which is illustrated in figure 3, there is a 10 second seizure in reference; the system detects 6 distinct short seizures. The STD considers the first event as a hit and all the remaining ones as FAs even when their midpoints fall within the duration of reference event. This implies that only one hypothesis event is accepted as a true detection. Consequently, the system has 1 TP and 5 FPs.

The other challenge of a similar case is shown in figure 4, where there are 5 distinct short seizures in reference and system detects one long seizure. The midpoint of the hypothesis falls within the range of third seizure event in reference. Therefore, the performance of the system is 1 TP, 5 FNs.



**Figure 3.** There are one True Positive(TP) and five False Negatives(FNs) and five False Positives (FPs) based on STD evaluation metric.

The STD algorithm is based on an overall assessment of metric parameters. Therefore, some information regarding the characteristics of the identified events, such as event duration, may be lost. Therefore, in this study, we propose an additional algorithm that calculates the fraction of duration of (1) detected event, (2) missed event and (3) False Alarm (FA). The performance of the system which is depicted in **Error! Reference source not found.** figure 1 based on the TAES is 0.5 TPs, 0.5 FNs and zero FP. Also, the performance of system in figure 3 presents 0.72 TPs and 0.28 FNs and 0 FP.

In TAES algorithm, the detection rate of a term is total duration of detected term divided by the total duration of reference term. Also, the miss rate is fraction of missing term over total duration of reference term. The FA is total duration of missed term divided by total duration of reference term. The TAES algorithm is formulated as follow:

 , (1)

 , (2)

(3)

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# Results

In this study, we investigate the characteristics five different deep learning based seizure detection systems based on different evaluation metrics. An EEG signal is input to the systems, typically in the European Data Format (EDF) file. The signal is converted to a sequence of feature vectors. A group of frames are classified into an event on a per-channel basis using combination of deep learning networks. The deep learning essentially looks across multiple epochs, which we refer to as the temporal context, and multiple channels, which we refer to as the spatial context since each channel is associated with a location of an electrode on a patient’s head. There are a wide variety of algorithms that can be used to produce a decision from these inputs. We explore five different deep learning systems, the comprehensive details about the architectures is available in [28], consisting of (1) hybrid of an HMM and a Stacked Denoising Autoencoder (SdA); (2) an HMM and a Long Short‑Term Memory (LSTM) network combination (3) compound of an Incremental Principal Component Analysis (IPCA) and a LSTM network; (4) a Convolutional Neural Networks (CNN) and a MultiLayer Perceptron (MLP) mixture; (5) hybrid of a CNN and LSTM networks. The reported results are based on the TUH EEG Seizure Corpus [29]. This dataset, which is publicly available, is a subset of the TUH EEG Corpus that focuses on the problem of seizure detection. A summary of the corpus (v1.1.1) is shown in table 1. A comparison of the performance of the different architectures is presented in table 2.

**Table 1.** An overview of the TUH EEG Seizure Corpus (V1.1.1).

|  |  |  |
| --- | --- | --- |
| **Description** | **Train** | **Eval** |
| Patients | 196 | 50 |
| Sessions | 456 | 230 |
| Files | 1,505 | 984 |
| Seizure (secs) | 51,140 | 53,930 |
| Non-Seizure (secs) | 877,821 | 547,728 |
| Total (secs) | 928,962 | 601,659 |

1. **Discussion**

In machine learning, finding suitable measures that show the characteristics of the system remains challenging. The commonly used and intuitive measure is accuracy which is formulated as:

 , (4)

The accuracy of the deep learning structures based on different evaluation metrics are depicted in table 3. The measure is not focusing on the specific class. The accuracy does not distinguish

**Table 2.** Performance of the deep learning systems based on different evaluation metrics on the TUH EEG Seizure Corpus.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Metric** | **HMM/ SdA** | **HMM/ LSTM** | **IPCA/ LSTM** | **CNN/ MLP** | **CNN/ LSTM** |
| **NIST STD** | **Sensitivity** | 30.35% | 26.73% | 24.73% | 29.52% | 30.18% |
| **Specificity** | 61.38% | 68.93% | 64.51% | 65.87% | 92.28% |
| **FAs/24 hrs** | 98 | 75 | 94 | 94 | 12 |
| **ATWV** | -0.8392 | -0.8469 | -0.4628 | -0.7971 | 0.1537 |
| **Any-overlap** | **Sensitivity** | 35.35% | 30.05% | 32.98% | 39.09% | 30.83% |
| **Specificity** | 73.35% | 80.53% | 77.58% | 76.84% | 97.10% |
| **FAs/24 hrs** | 77 | 60 | 73 | 77 | 6 |
| **DP Alignment** | **Sensitivity** | 44.11% | 33.77% | 35.77% | 43.35% | 32.13% |
| **Specificity** | 66.87% | 72.99% | 69.59% | 71.49% | 94.24% |
| **FAs/24 hrs** | 86 | 66 | 81 | 77 | 10 |
| **TAES** | **Sensitivity** | 17.67% | 22.94% | 23.08% | 32.12% | 11.33% |
| **Specificity** | 68.59% | 73.56% | 69.67% | 67.99% | 96.12% |
| **FAs/24 hrs** | 81 | 67 | 82 | 88 | 7 |
| **Epoch** | **Sensitivity** | 20.71% | 50.46% | 51.02% | 65.03% | 7.47% |
| **Specificity** | 98.22% | 94.82% | 94.09 | 91.55% | 99.84% |
| **FAs/24 hrs** | 1418 | 4133 | 4711 | 6738 | 125 |

between types of errors the system makes. This would be acceptable if the dataset is balanced. In the case of seizure and non-seizure detection system, the ignoring issue may lead to catastrophic accepting failure of the system. The issue is addressed by precision and recall and F-score measures. The precision and recall are computed as:

(5)

, (6)

The F- score convoy balance between precision and recall. The evenly balanced F-score, F1-score, is twice of the multiplication of precision and recall divided by the sum of precision and recall. The result of the deep learning systems based on F1-score is illustrated in table 4. They distinguish correct label classification within different classes. However, they do not indicate the true negative and specificity of the system.

The commonly accepted measures of reporting a performance of a system in clinical care application is sensitivity (TP/TP+FN), specificity (TN/TN+FP) and number of false alarms (FAs). These terms can be calculated based on different evaluation metrics. Each scoring metric performs optimally based on specific application revealing certain strength and weak points of a system. As an example, the overall behavior of each deep learning structures described can be inferred from table 2. Here, the operating points for each system has been selected to make results as comparable as possible, especially in terms of sensitivity and FA. Low sensitivity from Epoch-based scoring and moderate sensitivity from Any-Overlap method for HMM-SdA experiment suggests that the system is pruning to miss longer seizures.

**Table 3.** Accuracy of the deep learning structures based on different evaluation metrics.

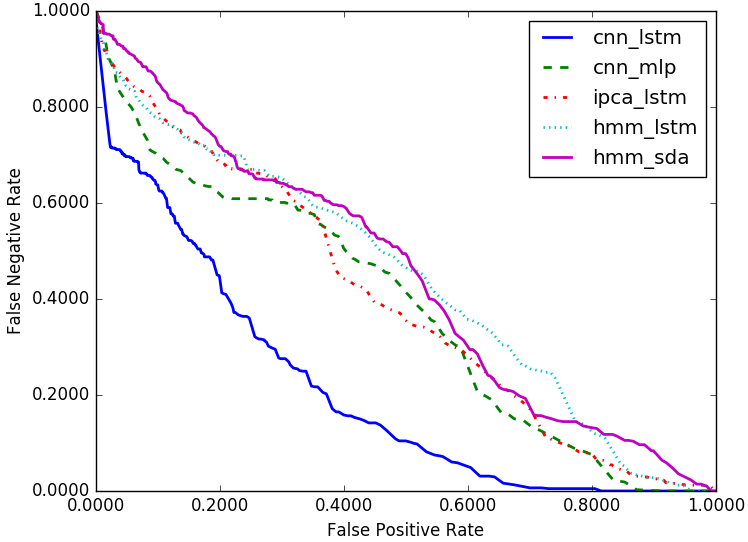
|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **HMM/ SdA** | **HMM/LSTM** | **IPCA/LSTM** | **CNN/ MLP** | **CNN/LSTM** |
| **NIST STD** | 53.95% | 54.00% | 52.14 % | 54.87% | 70.74% |
| **Any-overlap** | 65.11% | 66.54% | 65.63% | 66.85% | 78.94% |
| **DP Alignment** | 61.49% | 60.20% | 59.16% | 62.88% | 73.61% |
| **TAES** | 56.55% | 57.31% | 55.38% | 57.17% | 69.71% |
| **Epoch** | 92.34 % | 91.45% | 90.82 % | 89.54% | 91.46% |

Conversely, HMM-LSTM and IPCA-LSTM experiments with higher sensitivities according to Epoch-based scoring and lower sensitivities according to TAES, STD and Any-Overlap method implies that these systems tend to detect the longer seizures. Results of the CNN-MLP experiment, with relatively low sensitivity according to STD than any other scoring metric implies that midpoint of mostly detected seizures do not fall within reference transcription’s range. This suggests temporal misalignments implying either delay or early detection. Finally, CNN-LSTM with lower sensitivity according to TAES and Epoch-based scoring suggests that the system is detecting seizures with smaller durations only.

However, if system can have higher sensitivity if one is willing tolerance a poor specificity or a high false alarm. The sensitivity, specificity and false alarm should be balanced. The STD balances these measures by introducing an ATWV which assigns a reward to each correct detection and a cost to each incorrect detection. A perfect system has the maximum ATWV which is one. ATWV of system with no output is zero [30]. Negative TWV is feasible. This measure is useful when it is preferred to compare two systems based on a single number, though it is always better to compare DET curves over a range of operating characteristics. ATWV and DET curves are our recommended way to evaluate EEG interpretation systems. Based on results in table 2 and DET curve (figure 6) and results in table 2, CNN/LSTM system has the best ATWV because of highest sensitivity and lowest false alarms. The ATWV score is extremely poor for these systems largely due to the large emphasis this metric place on false alarms. The fundamental cause of having high false alarm is poorly detection of long events.

**Table 4.** F1-score of the deep learning structures based on different evaluation metrics.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **HMM/ SdA** | **HMM/LSTM** | **IPCA/LSTM** | **CNN/ MLP** | **CNN/LSTM** |
| **NIST STD** | 0.2399 | 0.2817 | 0.2431 | 0.2837 | 0.4171 |
| **Any-overlap** | 0.3053 | 0.3324 | 0.3395 | 0.3843 | 0.4452 |
| **DP Alignment** | 0.3511 | 0.3562 | 0.3516 | 0.4166 | 0.4472 |
| **TAES** | 0.1613 | 0.2566 | 0.2410 | 0.3115 | 0.1890 |
| **Epoch** | 0.2910 | 0.4729 | 0.4580 | 0.4858 | 0.1370 |



**Figure 4.** DET curves of all systems.

None of the conventional metric described here considers the fraction of the detected event; which is the inspiration behind the development of TAES scoring. This approach of TAES scoring makes scoring rules stricter than any other metric. Consequently, the performance scored using this scoring method tend to have lower sensitivity as shown in table 2. All mentioned evaluation metrics are perfectly correlated. The detail of how the sensitivities of metrics are correlated with each other is depicted in table 5.

**Table 5.** Correlation between sensitivity of the evolution metrics.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **NIST STD** | **DP Alignment** | **Any-overlap** | **TAES** | **Epoch** |
| **NIST STAD** | 1 | 0.832997 | 0.80882 | 0.602636 | 0.265321 |
| **DP Alignment** | 0.832997 | 1 | 0.976855 | 0.888646 | 0.668998 |
| **Any-overlap** | 0.80882 | 0.976855 | 1 | 0.911713 | 0.699448 |
| **TAES** | 0.602636 | 0.888646 | 0.911713 | 1 | 0.924567 |
| **Epoch** | 0.265321 | 0.668998 | 0.699448 | 0.924567 | 1 |

1. **Conclusion**
2. A common reason for clinical practices not relying on commercially available tools is due to their high FA rate. This has been confirmed by conducting series of interviews with certified neurologists around United States [21]. This is perhaps the single most important consideration today in guiding machine learning research applications in critical care. Critical care units are overwhelmed with the number of FA that the automated tools generate. To put this in perspective, one FA per bed within 1 hour in a 12-bed Intensive Care Unit (ICU) causes 12 interrupts per hour that must be serviced. This can easily overwhelm healthcare providers. Because there are many types of automated monitoring equipment used in an ICU setting, each yielding significantly high FAs, the number of FAs that must be serviced by healthcare providers is overwhelming [22]. As a result, clinicians who report that in practice simply ignore these systems [2].

Finding the proper evaluation metrics that shows the deficiency and strength points of a system is the main concern of researchers. In this paper, we began by introducing the current evaluation metrics in biomedical filed. Various evaluation scoring metrics possess their own strengths and weaknesses that shadow the analyze of recognition system’s behavior. Usually, researchers report the performance base on only one metric which cannot provide all the subtle details about the behavior of a system and can be misleading during development. The preferred way of measuring the scores is to select multiple scoring metrics and weigh the results based on specific application. We design the TAES scoring which simply scores the fraction hits, miss and FA on event basis. Also, we propose Average Term Weighted Value (ATWV) as a unique measure to balance the sensitivity, specificity and false alarm.

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