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AWARDS:

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TITLE: Automatic Interpretation of EEGs for Clinical Support

ABSTRACT BODY:

Introduction: Manual review of an EEG by a neurologist is time-consuming and tedious. Interrater agreement is low for annotation of low-level events such as spikes and sharp waves. A clinical decision support tool that automatically interprets EEGs can reduce time to diagnosis, reduce error and enhance real-time applications such as ICU monitoring. We present a high performance classification system based on principles of big data and machine learning.

Methods: A hybrid machine learning system was developed using a combination of hidden Markov models (HMMs) for sequential decoding and deep learning for postprocessing. The system detects three events of clinical interest: (1) spike and/or sharp waves, (2) periodic lateralized epileptiform discharges, and (3) generalized periodic epileptiform discharges. The system also detects three events used to model background noise: (1) artifacts, (2) eye movement and (3) background.

Results : A baseline system, originally developed to give high performance on the MIT-CHB Corpus, was evaluated on this task. This system, which consists of heuristics based on waveform properties, delivered a 99% detection rate with a 37% false alarm rate. It is not uncommon for such research systems to fail on clinical data. Clinicians have long complained about the high false alarm rates of such systems, and indicated a detection rate of 95% with a false alarm rate below 5% was required for clinical use of this technology. Our system produced a detection rate of 89% while maintaining a false alarm rate of 4%. The postprocessing also improved accuracy on spike detection from 25% to 55%.

Conclusion: Clinical use of such systems is limited due to poor classification performance – specifically a high false alarm rate. The existence of the TUH EEG Corpus provides for the first time a sufficient amount of data to apply powerful machine learning algorithms. As a result, performance is now approaching that required for clinical acceptance.