Remote monitoring and AI for detecting tardive dyskinesia and improving patient outcomes

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Purpose Tardive dyskinesia (TDD) is a common debilitating side effect of antipsychotic use and risk increases with age. Characterized most notably by involuntary facial movements such as grimacing, involuntary lip, mouth, and tongue movements, and eye blinking, TDD is difficult to treat and potentially irreversible. Psychiatrists and other mental health professionals are acutely aware of the impairment and disability experienced by patients who develop TDD. Early detection of TDD is critical so that appropriate interventions can be instituted. It is difficult for the most qualified diagnosticians to devote in-person time at the 4-6 times per year frequency necessary to provide every patient the 1) “active monitoring,” 2) discussion of results, 3) changes to medication and instructions expected with the urgent demands on every mental health professional today. This is increasingly challenging with the increase in telemedicine and patient populations and decreasing human resources due to the pandemic. Unfortunately, despite professionals’ best efforts, it is often too late in the process and the involuntary movements are permanent. A method for automatic TDD detection and accurate medication adherence would enable timely intervention and avoid patient stigma, lower quality of life, and expensive ongoing treatment for permanent TDD into late life. **Method** Forty-eight (n=48) participants at a northeast Ohio, USA mental health facility successfully completed a video recorded abnormal involuntary movement scale (AIMS) assessment and responses to six open-ended questions (i.e. “tell me about a pet you have had or one you’d like to have”) that were done seated and with hands visible on the desk. Each interview took approximately 30-minutes to complete. Four (n=4) other participants were excluded due to incomplete session data. The data set resulted in 268 video clips that could be used (48*6 = 268). Three trained professionals evaluated each participant’s video. Thirty-seven (37) of these 48 patients scored above zero on the AIMS scale. Convolutional neural networks (CNNs) are a deep learning architecture commonly used for analyzing visual imagery. Recurrent neural networks (RNNs) are an architecture using directed graphs that allow the representation of changes over time. CRNNs combine these architectures to allow analysis of imagery over time including movement. A CRNN architecture was applied in the current analysis of recorded semi-structured interview responses. **Results and Discussion** Results were measured using a common machine learning metric called the Receiver Operating Characteristics curve (ROC), a curve that compares Type 1 and Type 2 error rates. Any classifier is likely to suffer from Type 1 and Type 2 errors and there is a balance in choosing where to set the classifier threshold between positive and negative cases. To simplify this decision, a single number is calculated based on all possible thresholds, this is called the Area Under the Curve (AUC). An AUC of 0.5 indicates the model is essentially random while an AUC of 1.0 means it classifies each sample perfectly with no error. The TDtect model was initially trained with a training set and a hold-out set (20% of samples). The AUC for the preliminary model was 0.77. The algorithm will be improved with additional data collection.

References

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Keywords: mental health, artificial intelligence, medication adherence, tardive dyskinesia, remote patient monitoring
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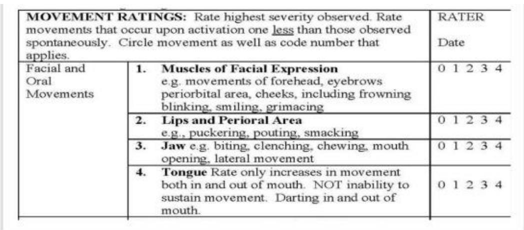
Acknowledgement Funding for this research was provided in part by the National Institute of Mental Health



MOVEMENT RATINGS: Rate highest severity observed. Rate movements that occur upon activation one less than those observed spontaneously. Circle movement as well as code number that applies.		RATER Date
Facial and Oral Movements	1. **Muscles of Facial Expression** e.g. movements of forehead, eyebrows periorbital area, cheeks, including frowning blinking, smiling, grimacing	0 1 2 3 4
	2. **Lips and Perioral Area** e.g., puckering, pouting, smacking	0 1 2 3 4
	3. **Jaw** e.g. biting, clenching, chewing, mouth opening, lateral movement	0 1 2 3 4
	4. **Tongue** Rate only increases in movement both in and out of mouth. NOT inability to sustain movement. Darting in and out of mouth.	0 1 2 3 4

Figure 1— (Left) The proposed TDtect system will utilize combination detection algorithms to summarize behavior components such as blinking, grimacing, and tongue visibility to determine a prediction of an individual as TDD positive or TDD negative. Three psychiatrists receiving additional TDD observation training will use the standardized TDD instruments to evaluate the same video. (Right).