Detecting Depression Using a Framework Combining Deep Multimodal Neural Networks with a Purpose-Built Automated Evaluation

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Abstract

Machine learning (ML) has been introduced into the medical field as a means to provide diagnostic tools capable of enhancing accuracy and precision while minimizing laborious tasks that require human intervention. There is mounting evidence that the technology fueled by ML has the potential to detect, and substantially improve treatment of complex mental disorders such as depression. We developed a framework capable of detecting depression with minimal human intervention: AiME (Artificial Intelligence Mental Evaluation). AiME consists of a short human-computer interactive evaluation and artificial intelligence, namely deep learning, and can predict whether the participant is depressed or not with satisfactory performance. Due to its ease of use, this technology can offer a viable tool for mental health professionals to identify symptoms of depression, thus enabling a faster preventative intervention. Furthermore, it may alleviate the challenge of interpreting highly nuanced physiological and behavioral biomarkers of depression by providing a more objective evaluation.

Keywords: depression, artificial intelligence, deep learning, mental health evaluation, multimodal classification

Introduction

Machine learning (ML), a method of data analysis in which computers “learn” to independently modify or adapt their actions (e.g., make predictions) to produce more accurate decisions and results, has emerged as a powerful analytic tool for large and complex datasets (Marsland 2011). As such, ML lends itself to the processing of disease biomarkers and has been implemented in medical diagnostic tools ranging from the detection and classification of tumors (Petricoin and Liotta 2004; Bocchi et al. 2004), to providing a differential diagnosis of neurodegenerative diseases with similar presentations (Salvatore et al. 2014). ML methods have reliably demonstrated an increase in prediction accuracy when compared with older, more conventional statistical techniques or physician-based expert systems (Cruz and Wishart 2006).

In parallel, ML techniques have been applied to examine affective display differences exhibited during emotion states, such as facial expression and vocal prosody, through audio and video-based analysis. These advances have generated a new field of research which has successfully used ML techniques, such as support vector machines (Cohn et al. 2009), regression (Valstar et al. 2013), and neural networks (shallow and deep; (L. Yang et al. 2017)), for automatic recognition of emotion using audiovisual data from conventional databases (Schuller, Steidl, and Batliner 2009; Burkhardt et al. 2005) and recently more naturalistic environments (Dhall et al. 2013; McKeown et al. 2012; Ringeval et al. 2013). Moreover, ML has also been extended to investigate verbal and nonverbal affective abnormalities associated with psychiatric disorders and has gone on to successfully classify those presenting with and without a given diagnosis (Hamm et al. 2011; P. Wang et al. 2008). This is a substantial advancement given that prior to the advent of ML, identifying divergences in affect-related behaviors relied exclusively on labor-intensive, rater-based analysis (e.g., Gaebel and Wölwer 1992), thus leaving findings more susceptible to bias.

ML-based techniques show incredible promise for psychiatric diagnostics through harnessing observable affect-related behaviors through highly objective methods. In fact, observable affect-related behaviors are commonly used by mental health professionals to assist in psychiatric diagnostics, often through non-structured methods that result in general, qualitative data (e.g., ‘flat’ or ‘broad’ affect). However, the majority of current algorithms still require some level of human intervention such as labor-intensive manual labelling or hand classification of data in order to extract useful features prior to analysis (Valstar et al. 2013; Valstar et al. 2014). These steps render current algorithms-based analysis time-consuming as well, ultimately hampering feasible application of current ML techniques in clinical settings.

We sought to investigate the possibility of developing a method that combines advanced ML-based techniques in combination with automated data collection procedures to identify clinical depression in a demographically diverse population. We chose to begin this effort with depression for two reasons. First, the prevalence and impact of depression is staggering. Depression is *the* leading cause of disability in the United States for individuals ranging from 15 to 44.3 years of age (NIMH). Major depressive disorder (MDD), a psychiatric disorder characterized by experiencing depressed mood or anhedonia most of the day nearly every day for a period of two weeks or more, affects upwards of 16.1 million American adults annually, roughly 6.7% of the United States population (NIMH). Distress from clinically elevated depression is often accompanied with suicidal ideation and attempt (WHO). Nearly 800,000 individuals worldwide die as the result of suicide each year, making it the second leading cause of death in individuals 15 to 29 years of age. Second, verbal and nonverbal affective abnormalities demonstrated by individuals with depression are well-documented and lend themselves to ML-based processing. Depressed individuals possess significant differences in facial expressions (Girard and Cohn 2015) and everyday vocabulary use (e.g., absolutist words; (Al-Mosaiwi and Johnstone 2018)) when compared with healthy individuals. In addition, speaking behaviors and voice acoustic characteristics (e.g., F_0 and switching pauses; (Y. Yang, Fairbairn, and Cohn 2013)) have been closely linked to depressive state, recovery time course from depression (Kuny and Stassen 1993) and treatment response (Mundt et al. 2007). This research provides a solid foundation of 'behavioral biomarkers' that may be used to identify clinically elevated depression using audiovisual data.

Hence, we designed a web-based evaluation that can be completed quickly (~5 min), and requires no manual labeling that takes into account all of the above-mentioned modalities. In addition, we created a new ML-based algorithm that leverages, and extends, the behaviorally relevant findings to identify depression using naturalistic audiovisual data. This comprehensive methodology (AiME) was developed to minimize human intervention, thereby enhancing feasibility, scalability, and potential applications in clinical settings.

Methods

Participants

We collected data from 671 participants who performed a human-computer interactive evaluation. The evaluation was primarily composed of interview questions where participants were recorded by a webcam and a microphone while they responded to questions relating to their mental well-being. The evaluation also contained an anonymous demographics questionnaire (age, sex, ethnicity, etc.) as well as a brief, multiple-choice, mental health questionnaire in order to provide additional data and ground-truth validation. Participants were asked to confirm whether recording specifications (lighting, camera angle, etc.) were appropriate. The evaluation took approximately five minutes, and data from the demographics questionnaire, video responses, and mental health questionnaires were stored and accessed in accordance with HIPAA compliance standards. The resulting sample of participants was 58.0% female, 41.7% male and 0.3% other; 73.8% White, 10.1% African-American, 8.3% Hispanic/Latino, 4.5% Asian/Pacific Islander, 0.6% Native American, 0.4% Middle Eastern, and 2.2% who identified with “other” ethnicity category.

Measures

Video questions. Participants responded vocally to eight questions regarding current mental well-being for 15–60 seconds per question (*e.g.*, “What has been frustrating you lately?”). Similarly, participants responded vocally to five questions regarding past and current treatment history for 3–30 seconds per question (*e.g.*, “Has a mental health professional diagnosed you with depression in the past?”). During these questions, video and audio data were collected. Participant’s behavioral data recorded via video and audio, as well as speech content (what was said) were combined with the demographics data and used for prediction.

Depression. Participants completed the Patient Health Questionnaire (PHQ-9)(Kroenke, Spitzer, and Williams 2001), which is a 9-item self-report measure that assesses depression on a 4-point scale (from 0 = not at all to 3 = nearly every day). Total scores range from 0-27 with higher scores denoting a greater endorsement of depressive symptoms, and scores ≥ 10 indicating that a respondent may be depressed. Scores from PHQ-9 were used as the "ground truth for the training and assessment of ML models (see below).

Statistical Approach

We developed a multimodal deep learning model that used video data, audio data, and word content from participants' responses, as well as demographics and other metadata. These data were used as adjacent inputs to the model to perform binary classification on whether participants were depressed. Data processing involved the following steps: 1) Video data was subsampled to 8 frames per second, cropped to participants' face (using Google Cloud Vision), then down-sampled to 128x128 pixels (Figure 1A), and finally analyzed using an architecture resembling ResNet (He et al. 2016). 2) Audio data from the microphone was down-sampled to 80Hz and 22 features were extracted over the entire time trace. These features included 13 Mel-frequency cepstral representations, as well as other features such as spectral roll-off, entropy, etc. (Figure 1A). 3) Speech content was automatically transcribed using Google Cloud Speech service, and transformed to word representation vectors using Global Vectors (GloVe 6B)(Pennington, Socher, and Manning 2014)—used as another input to the model (Figure 1A). These data streams underwent Long Short-Term Memory (LSTM) recurrent neural network (RNN) (Hochreiter and Schmidhuber 1997) layers due to the time varying nature of the inputs. Lastly, the model combined these inputs with a dense layer containing demographic information and other metadata, and prediction occurred after the application of dense layers (Figure 1B).

Furthermore, we applied data augmentation, a commonly used method that simultaneously increases the number of input data points as well as reduces the potential for overfitting the model (i.e., make the outcome invariant to geometric and color properties of individual images)(J. Wang and Perez 2017). In particular—in addition to providing raw video to the model—we 'mirrored' the video (geometric), adjusted color contrast, and normalized pixel values (color). Lastly, the scores from the PHQ-9 were used as the ground truth such that a PHQ-9 score of 10 was used as a threshold for depression. Computations were implemented using Keras with a TensorFlow backend. We experimented with three variations of our model that allowed us to compare performances within our framework and with results from prior work in the literature. These variations include two binary classification models as well as a regression model, all of which will be described in detail below.

The classification models were trained on 365 exams using a binary cross-entropy loss function and an independent set of 91 exams were left for a testing phase. In addition, we used early stopping (Yao, Rosasco, and Caponnetto 2007), a regularization method to avoid overfitting the training data. The output of the model (predicted y) was rounded to construct a binary vector consisting of ones (depressed) and zeros (non-depressed) and was compared against the true values (true y)—another binary vector built from the PHQ-9 scores (as explained above). The second classification model was different from the first in that we also performed hyperparameter optimization using random search (Bergstra and Bengio 2012) and we used bidirectional LSTM (BiLSTM) in lieu of LSTM.

Results

We used various metrics to evaluate the model performance at each epoch (Fabian et al. 2011). First, we quantified the receiver operating characteristics (ROC) curve and the area under that curve (AUC)—common measures of model performance in classification (Jin Huang and Ling 2005)—for each model, as well as individual epochs within a model (Figure 2). Indeed, our model successfully classified depressed versus non-depressed individuals well above chance level.

Moreover, we constructed the confusion matrix consisting of the number of true positives (*TP*; correctly identified as depressed by the model), true negatives (*TN*; correctly identified as non-depressed by the model), false positives (*FP*; non-depressed individuals that were identified as depressed by the model), and false negatives (*FN*; depressed individuals that were identified as non-depressed by the model). These values were used to compute the following metrics to further gauge the model performance (for a detailed description, see Table 1):

a) Accuracy: $\frac{TP+TN}{TP+TN+FP+FN}$

b) Precision: $\frac{TP}{TP+FP}$

c) Recall (Sensitivity): $\frac{TP}{TP+FN}$

d) Specificity: $\frac{TN}{TN+FP}$

e) F-1 score: $\frac{2}{\frac{1}{precision}+\frac{1}{recall}}$

According to the utilized metrics, the described models exhibited satisfactory performance levels. The second model (random search) outperformed the first model (data not shown) and achieved high and stable performance across all measures (Table 1). It is worth noting that, here, we treated data from individual responses to questions (within an evaluation) as independent observations. However, when data from individual participants were aggregated, model performance measures were within the bounds reported in Table 1 (e.g., accuracy = 69.23). Two representative epochs reached high specificity and sensitivity values (87.77% and 86.81% respectively) and in fact, it is possible to adjust the threshold value (τ) at which a prediction is considered positive to achieve desired levels of specificity and sensitivity (Table 1). It has been argued that it is important to report diagnostic test results at different thresholds, particularly for binary classification problems, since the clinical relevance and optimal threshold values will likely depend on the type of diagnostics performed (Mallett et al. 2012). Thus, it is possible to combine predictions from two separate tests within an individual with other relevant contextual information to provide more comprehensive diagnostics and care.

Recently, accurate evaluation of depression and other mental illnesses from behavioral biomarkers using automated methods has gained popularity and momentum (Gratch et al. 2014; Alhanai, Ghassemi, and Glass 2018). Thus, it is necessary to be able to compare the performance of our model with prior work in the literature. Given that the majority of those methods use a regression model (as opposed to a binary classifier), we implemented a modified version of our model to perform a regression against the PHQ-9 scores (0–27) for the purposes of comparison. To achieve this, the sigmoid output function of the model was multiplied by 27 (the maximum value obtain from PHQ-9 scores (i.e., the model was trained against labels that ranged from 0 to 27); and a mean squared error loss function was used in lieu of a binary cross-entropy function. We used mean absolute error (MAE) and root mean square error (RMSE) as measures for model evaluation that also allowed for comparisons with previously described models (Table 1). Although the use of different scales for training (e.g., Yang *et al.* 2017 used PHQ-8 scores) can introduce potential confounds for performance comparisons, we scaled our model's MAE and RMSE values to obtain an error percentage. When we compared error percentages, we found that our model fared better in terms of MAE compared to previous models and performed comparably with respect to RMSE percentage (L. Yang et al. 2017). It is noteworthy that this difference in performance might arise because of a difference in the distribution of the original scores (whether the datasets contain more depressed participants).

Discussion

In this manuscript we have introduced a novel methodology, which combines a brief evaluation and ML techniques to detect depression. Our model takes advantage of the fact that there are significant differences in facial expressions, tone of voice, and vocabulary used by individuals with depression compared to the non-depressed population. Our results suggest that it is possible to detect depression (or a depressive state) with methods that require minimal human intervention both in terms of data collection and data labelling. It must be borne in mind that despite having achieved high performance levels, there are some challenges and limitations that will be detailed below.

One limitation of the current approach is that because the self-report exam is conducted at specific moments in time, the behavioral results might be the individual's state-dependent affect (a short-term emotional influence caused by an immediate event), rather than the long-term affective characteristics associated with depression. Due to the brief nature of the exam, however, we anticipate that the evaluation can be taken multiple times—for example at periodic time intervals—which can mitigate the state-dependent affect. Completing the evaluation at periodic time intervals may also offer two additional benefits: a longitudinal assessment of the depressive state, and insights into subtle depressive symptom changes over time. Another limitation—which is a common caveat of supervised learning methods—is that in order to train the model to perform a classification task, data needs to be labelled into different categories (i.e., depressed versus not depressed). In our algorithm, the "ground truth" is determined based on applying a threshold on the self-reported, and therefore subjective, PHQ-9 scores. Nonetheless, it is possible to expand upon the current method, and utilize labels provided by psychiatrists and mental health specialists to obtain better, and more accurate, performance measures.

Taken together, the current study presents a paradigm that can facilitate the use of new techniques in a clinical setting. For instance, given that conditions such as depression and anxiety are highly correlated, it is plausible for future studies to apply the methodology described in the current manuscript to predict anxiety. As such, it can pave the way for future studies that will use behavioral biomarkers to identify various other psychiatric disorders (e.g., schizotypy). Lastly, neuro-technologies (*e.g.*, chronic brain implants) have emerged as viable options that use electrophysiological biomarkers to treat psychiatric diseases such as depression. AiME can be used along with these neuromodulation techniques—such as the application of deep brain stimulation and transcranial magnetic stimulation to treat pharmaco-resistant depression (Bewernick et al. 2010; George et al. 2000)—to provide more powerful therapeutic approaches on the one hand, and elucidate the relationship between the brain activity and behavior on the other hand.

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Table 1

Summary of Various Measures Used for the Evaluation of Model Performance.

Model 1 Performance Metrics (Classification) **Balanced Models** ($\tau = 0.41$)				
Accuracy	**Precision**	**Recall**	**Specificity**	**F-1 Score**
68.02 ± 1.88 **<u>70.88</u>**	68.61 ± 5.77 **<u>80.46</u>**	68.59 ± 10.75 **<u>86.81</u>**	67.46 ± 12.96 **<u>87.77</u>**	67.66 ± 3.20 **<u>71.15</u>**
Selected Balanced Model ($\tau = 0.48$)				
70.26	69.88	70.07	70.45	69.97
90% Specific Model ($\tau = 0.63$)				
70.16	82.93	49.93	**89.95**	62.33
90% Sensitive Model ($\tau = 0.28$)				
61.40	56.96	**89.79**	33.63	69.70
Model 2 Performance Metrics (Regression Error)				
Train MAE	**Train RMSE**	**Test MAE**	**Test RMSE**	
5.54 (20.52%)	6.90 (25.56%)	5.59 (20.71%)	6.88 (25.48%)	

Values from the first model are reported as mean ± standard deviation (n = 25) and were computed during the test phase (i.e., unseen data). Underlined values in bold indicate the highest values obtained from different model epochs. Parameter τ represents the threshold at which the predictions were considered positive.

For the second model measure, the numbers inside parentheses represent the percentage of error with respect to the range of possible values (27 for PHQ-9 scores), thus lower numbers indicate better performance.

Model 1 training:

Number of participants = 365; Number examples = 2920; Examples after augmentation = 11680

Model 1 testing:

Number of participants = 91; Number examples = 728; Examples after augmentation = 2912

Model 2 training:

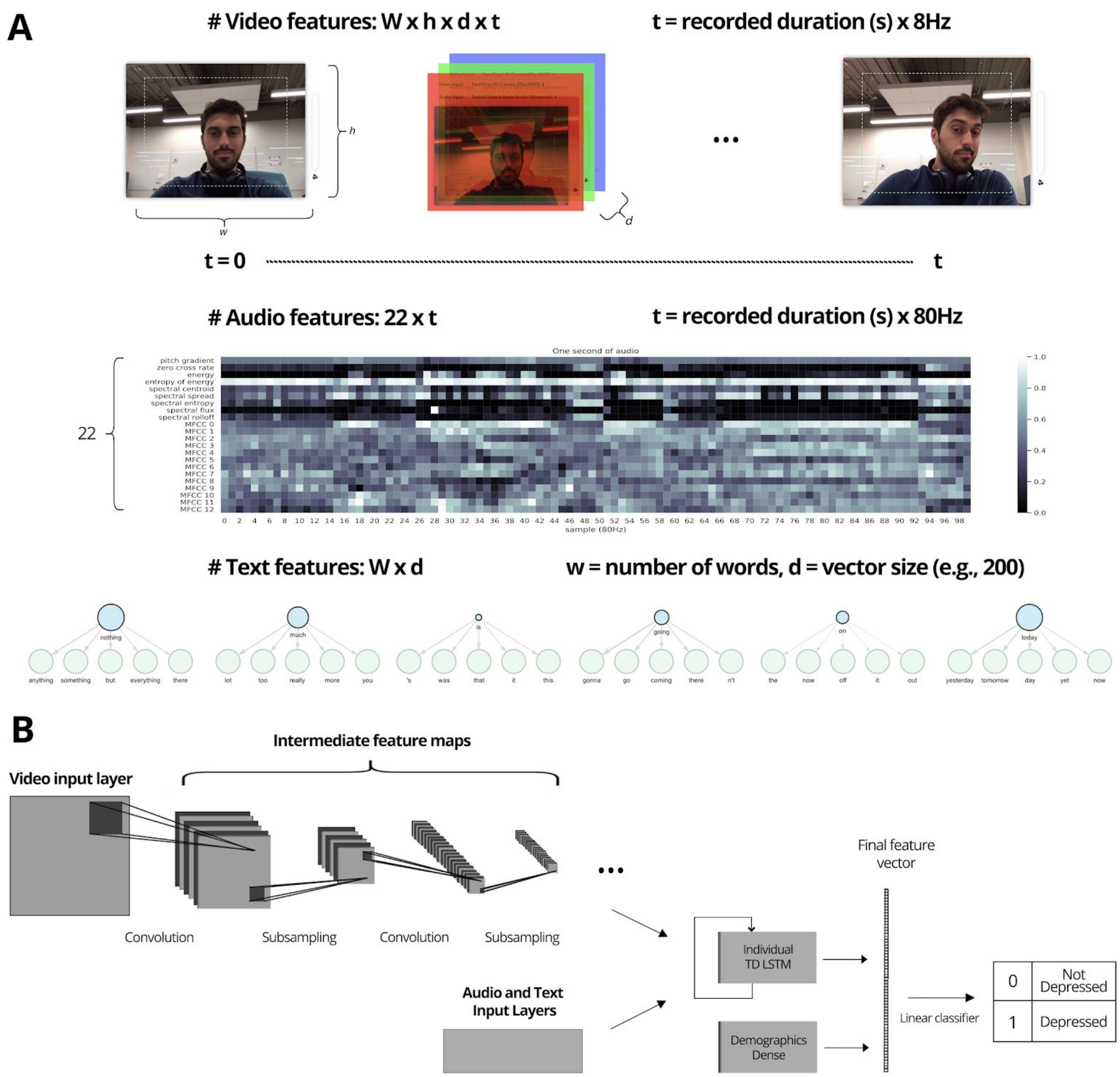
Number of participants = 537; Number examples = 4296; Examples after augmentation = 17184

Model 2 testing:

Number of participants = 134; Number examples = 1072; Examples after augmentation = 4288

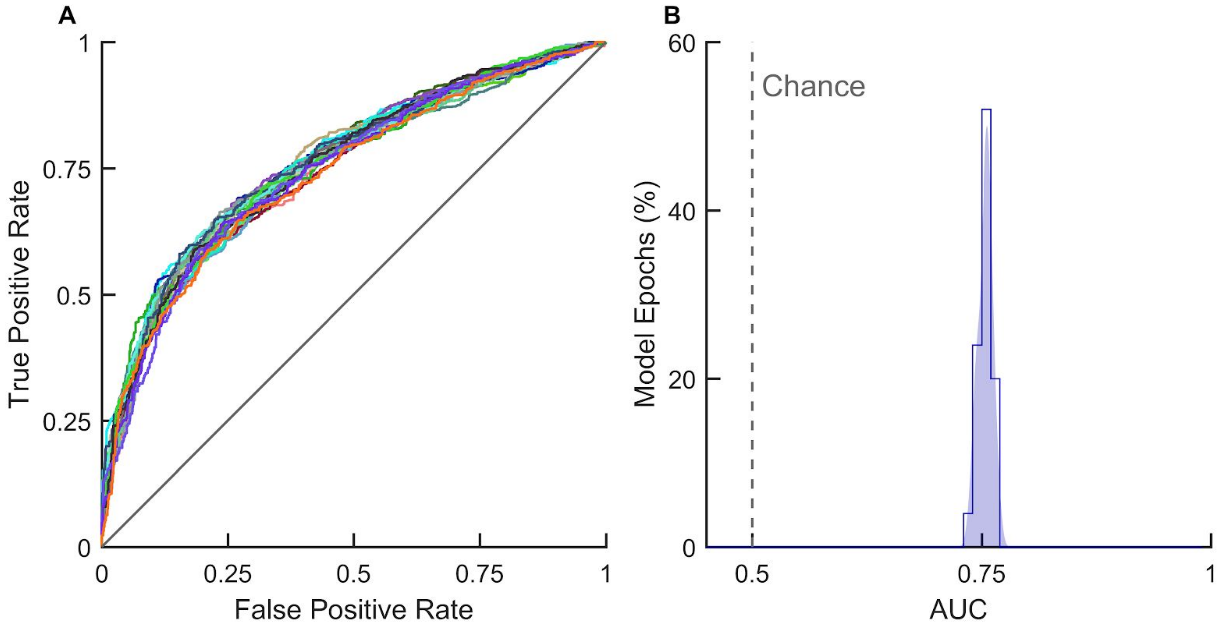
Figures and Figure Captions

Figure 1: Inputs and the Architecture of the Network Used for Classification.



(A) Example inputs from three different modalities (video, audio, text). Top) video data consisted of frames whose dimensions were in 128x128 pixels in width and height, and 3 in depth (corresponding to the RGB color channels). Depending on the total length of the video, the number of video frames per sample also varied (8 frames per second). Middle) Audio data, similar to video data, consisted of frames (80 per second) that were transformed into 22 features (see text), including short-term power representations (mel-frequency cepstrum). Bottom) Text data was analyzed using GloVe representation with a word vector size of 200 (see text), thus leading to input dimensions of number of words x 200. **(B)** An overview of the network demonstrating how different data streams are processed individually and combined. A sigmoid activation function was used on the output of the last dense layer for binary classification.

Figure 2: Classification Achieved Performances well above Chance Level.



(A) Receiver operating characteristics (ROC) curve obtained from 25 representative test epochs from a model (gray lines) indicating that classification was done above chance level (red diagonal line). **(B)** The distribution of the area under the ROC curve (AUC) values (mean ± std = 0.75 ± 0.01) for the curves shown in (**A**). Red dashed vertical line indicates chance level. These metrics are derived from predictions made during the test phase (i.e., unseen data).