EarlyScreen: Multi-scale Instance Fusion for Predicting Neural Activation and Psychopathology in Preschool Children

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Emotion dysregulation in early childhood is known to be associated with a higher risk of several psychopathological conditions, such as ADHD and mood and anxiety disorders. In developmental neuroscience research, emotion dysregulation is characterized by low neural activation in the prefrontal cortex during frustration. In this work, we report on an exploratory study with 94 participants aged 3.5 to 5 years, investigating whether behavioral measures automatically extracted from facial videos can predict frustration-related neural activation and differentiate between low- and high-risk individuals. We propose a novel multi-scale instance fusion framework to develop EarlyScreen – a set of classifiers trained on behavioral markers during emotion regulation. Our model successfully predicts activation levels in the prefrontal cortex with an area under the receiver operating characteristic (ROC) curve of 0.85, which is on par with widely-used clinical assessment tools. Further, we classify clinical and non-clinical subjects based on their psychopathological risk with an area under the ROC curve of 0.80. Our model's predictions are consistent with standardized psychometric assessment scales, supporting its applicability as a screening procedure for emotion regulation-related psychopathological disorders. To the best of our knowledge, EarlyScreen is the first work to use automatically extracted behavioral features to characterize both neural activity and the diagnostic status of emotion regulation-related disorders in young children. We present insights from mental health professionals supporting the utility of EarlyScreen and discuss considerations for its subsequent deployment.

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2474-9567/2022/6-ART60 $15.00
https://doi.org/10.1145/3534583

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing systems and tools**; • **Computing methodologies → Machine learning**; • **Applied computing → Psychology**; **Health informatics**.

Additional Key Words and Phrases: mental health, neuroscience, computer vision, affective computing

ACM Reference Format:
Manasa Kalanadhabhatta, Adrelys Mateo Santana, Zhongyang Zhang, Deepak Ganesan, Adam S. Grabell, and Tauhidur Rahman. 2022. EarlyScreen: Multi-scale Instance Fusion for Predicting Neural Activation and Psychopathology in Preschool Children. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 6, 2, Article 60 (June 2022), 39 pages. https://doi.org/10.1145/3534583

1 INTRODUCTION

Emotion regulation – the ability to modulate the duration, valence, or intensity of an emotional experience [61] – is one of the most widely studied topics in neuroscience and psychology. Researchers have examined emotion regulation capabilities among infants [26], young children [34, 56], adolescents [25], as well as adults [17]. In particular, poor emotion regulation, particularly in response to negative emotional challenges such as frustration, is a core feature of some of the most commonly diagnosed psychological disorders that persist across the lifespan, such as attention deficit hyperactivity disorder (ADHD) [13, 114], childhood depression [80], pediatric bipolar disorder [81], and a range of other psychopathological disorders [65, 91, 92, 99].

Problems with emotion regulation emerge early in life, are closely tied to early-onset psychological disorders that disrupt children's functioning, persist into later stages of development, and exert an enormous financial burden on society [16]. There has been particular interest in studying emotion regulation during the preschool years, when this ability develops rapidly and has a profound effect on children's capacity to function adaptively in school, home, and social environments. Early childhood emotion regulation is essential for academic achievement [60] as well as for the formation of early friendships [46]. Poor emotion regulation predicts over a dozen DSM-5 disorders and is the most common reason young children are referred to psychological services [8].

Despite the urgent need to identify these psychological disorders early, most commonly used diagnostic instruments such as standardized questionnaires and semi-structured clinical interviews are long or expensive to administer [88] and have surprisingly poor accuracy compared to diagnostic tools used in physical medicine [106, 115], with area under curve (AUC) values in the 0.7-0.8 range [21, 69]. The difficulty in achieving high diagnostic accuracy stems in part from the fact that signs of problematic emotion regulation, such as temper tantrums, are difficult to distinguish from normative misbehavior young children commonly exhibit [123]. This creates a 'when to worry' problem where caregivers lack guidelines to determine the severity and clinical significance of a child's behavior. Furthermore, attaining a psychological diagnosis typically requires families to overcome several barriers in order to seek clinical care, including awareness, cost, and labor burdens [24]. "Gold standard" diagnostic tools also require specialized training and clinical services, are extremely time intensive, and therefore difficult for clinicians to implement in community settings [74, 105].

There is an opportunity for next-generation diagnostic instruments to identify not just psychological disorders, but abnormalities in the neurobiological mechanisms that drive them. Neuroimaging work over the past few decades has led to major advances in identifying the neural mechanisms underpinning the emotion regulation response and driving symptoms of psychopathology [59]. Several studies link decreased neural activation in the lateral Pre-Frontal Cortex (LPFC) to poorer emotion regulation and higher aggressive behavior [32], and dysfunctional LPFC activation to depression and ADHD [36, 78]. However, neuroimaging via functional Magnetic Resonance Imaging (fMRI) is expensive and also especially unsuitable for young children, as it requires them to lie completely still in the scanner for extended periods of time. Techniques such as functional Near-Infrared Spectroscopy (fNIRS) provide a more comfortable alternative but remain prohibitively expensive for diagnostic screening at a large scale. Therefore, most neuroimaging studies are restricted to in-laboratory observations of relatively few participants and mental health practitioners have to rely on questionnaires for diagnostic

purposes. We investigate whether it is possible to leverage automatically extracted behavioral features from video cameras to develop novel and more informative tools to support clinical diagnosis. Prior research suggests that neural activation during emotion regulation could be indirectly measured via cameras in two ways. The first is via facial expressions, which researchers have found to be strong behavioral correlates of emotion regulation in children [33, 108, 137]. Certain expressions such as a Duchenne smile (see [47]) or a frown during emotion regulation have been shown to be correlated with neural activity in the lateral and medial prefrontal cortex and the amygdala [58, 64, 103] – regions of the human brain known to be associated with emotion regulation [22, 37, 114, 119]. The second is via eye and bodily movement-related measures, which have been identified as potential biomarkers for ADHD diagnosis [7, 82, 83]. Gaze fixations have also been shown to predict neural activation during emotion regulation [120].

In this paper, we develop EarlyScreen, a set of video-based diagnostic tools that have the potential to be deployed outside clinical settings to (a) unobtrusively infer coarse-grained neural activation in the LPFC during emotion regulation without neuroimaging, and (b) identify individuals who exhibit clinically significant psychopathological symptoms without requiring the administration of diagnostic questionnaires. Automatically detecting psychopathology and it's underlying neural abnormalities from behavioral markers would enable the development of new, groundbreaking clinical tools with important implications for childhood mental health practitioners. It also sets the stage for highly effective and scalable mental health screening tools that can be deployed on personal devices in the future.

We conduct a study with 94 participants where we record Pre-Frontal Cortex (PFC) activation using functional Near-Infrared Spectroscopy (fNIRS), which detects hemoglobin changes in the outer cortex using near-infrared light. We use simultaneous video recordings to extract individual anatomical facial muscle movements, or action units (AUs), that children display throughout the duration of a clinically validated emotion regulation task. We also track changes in head pose and eye gaze in order to quantify gross movement and fidgets exhibited by children during the task. We then utilize AU and movement features to coarsely predict PFC neural activation and to differentiate children with and without clinical levels of psychopathological risk.

A key challenge that we encounter in doing so is that of classifying individuals into groups based on a single label per individual. Despite the large amount of behavioral data for each individual, there is only one label corresponding to the individual's PFC activation and psychopathology risk, respectively. This leads to underutilization of raw data in a supervised learning setting, where multiple observations or episodes of data from each individual have to be condensed into a single feature vector. Doing so results in loss of information about the similarities and differences between these episodes. We examine whether such independent observations can be utilized to extract useful fine-grained features in addition to coarse-grained aggregates.

To this end, we develop a novel Multi-scale Instance Fusion (MIF) framework that leverages coarse-grained labels in a supervised learning setting to learn from both coarse- and fine-grained features. Our framework results in significant performance improvement compared to baseline supervised learning models at both classification tasks described above, i.e., low vs. normal neural activation and clinical vs. non-clinical risk detection. The MIF framework could also be utilized in a range of other settings where multiple episodes of data are observed corresponding to a single supervised learning instance.

To summarize, the following are the major contributions of our work:

- We conduct a multimodal study involving 94 participants aged 3.5 to 5 years, recording neural activation through fNIRS and facial expressions, gaze, and movement using videos during a frustration-inducing task.
- We propose a novel machine learning framework – Multi-scale Instance Fusion – to leverage coarsely labeled video data for predicting neural activation and psychopathology.
- We show that our proposed model can classify individuals with normal vs. low PFC activation levels using facial AUs, achieving an area under the receiver operating characteristic (ROC) curve of 0.85 and sensitivity

= 0.75 and specificity = 0.77 respectively. The performance of our model is comparable to previous work predicting measures of brain activity from longitudinal, passive mobile sensing features [98] and is on par with that of widely used symptom-based clinical diagnostic tools [128]. In contrast, EarlyScreen uses an active, clinically validated task of a short duration that can be deployed outside clinical settings.
- We use facial AUs and movement-related features to classify clinical vs. non-clinical individuals based on psychopathological risk. Our model achieves an area under the ROC curve of 0.80, with a sensitivity of 0.72 and a specificity of 0.76. We show that our model predictions are correlated with scores on various commonly used clinician-administered assessment scales.
- We discuss various considerations for deploying EarlyScreen in the wild on mobile devices, including ethical considerations, model performance across demographic subgroups, and tolerance to noisy real-world conditions. We also describe a pilot implementation of our task on a tablet, as well as insights from a survey of 60 mental health professionals who evaluated the utility and drawbacks of EarlyScreen.

To the best of our knowledge, EarlyScreen is the first attempt towards characterization of neural activation during emotion regulation in an automated, non-invasive manner. Our findings underscore the potential for using mobile and ubiquitous technologies to measure neural activation in the real world and make mental health diagnoses. While our study was conducted in a lab setting to support fNIRS data collection, EarlyScreen can, in future, be gamified into mobile mental health screening tools that can be deployed outside clinical settings to support existing diagnostic practices.

2 RELATED WORK

2.1 Neural and Behavioral Responses to Emotion Regulation

Emotion regulation has long been studied as a symptom and major causal factor of psychopathology, especially in developmental psychology literature. It has been associated with a range of mental disorders including ADHD [13, 114], childhood depression [80], pediatric bipolar disorder [81], and mood and anxiety disorders [65, 92]. Improving emotion regulation is also a major target of treatment success in psychopathology and psychotherapy theories [80]. However, distinguishing between emotion dysregulation and normative misbehavior in early childhood is a challenging problem, as children commonly exhibit dysregulated behaviors such as temper tantrums due to their young age [122].

This has led to considerable interest in trying to understand the neural underpinnings of emotion regulation. Davidson et al. observed cerebral asymmetry using electroencephalography (EEG), with emotions related to approach and withdrawal producing anterior activation in the left and right hemispheres, respectively [37]. stimulus [70]. Urry et al. discovered that a stronger amygdala response corresponds to an enhancement or up-regulation of the negative emotion, while lower amygdala response is associated with effective down-regulation. Ventromedial PFC activation was also inversely coupled with that of the amygdala [119]. Perlman et al. found that young children with higher parent-assessed frustration levels exhibited higher dorsolateral PFC activation [103]. Grabell et al. showed that LPFC activation exhibited a quadratic relationship with irritability, and decreased with increasing irritability in children with severe symptoms [59]. Generally, the lateral PFC has been hypothesized to be important for frustration regulation during early childhood [58, 103], which led us to focus on examining neural activation in the lateral PFC in our work.

Recent findings also suggest the possibility of accurately inferring PFC activation during frustration from a range of behavioral markers. Ekman et al. observed that certain facial expressions, such as the Duchenne smile, are associated with the EEG asymmetry described above [47]. The intensity of frowning in response to negative stimuli was negatively correlated with activation in the ventromedial PFC [64]. Grabell et al. found that both positive and negative expressions with eye constriction during a frustration-inducing task were associated with

lateral PFC activation and emotion regulation [58]. However, our work is the first to successfully leverage these facial markers to *predict* neural activation.

Studies have also found differences in measures related to eye movement [82, 83] and bodily movements [7] between participants with and without ADHD. Similarly, gaze fixations have been shown to predict neural activation during emotion regulation [120]. Based on these observations, our work aims to use unobtrusively monitored facial expressions, eye gaze, and movement-related behaviors from videos to predict neural activation in the prefrontal cortex as well as psychopathological disorder status among young children engaged in a frustration-inducing task.

2.2 Quantifying Behavioral Markers

Researchers have long shown interest in measuring and understanding the facial behavior of human subjects. However, human measurement of facial expressions is likely to be influenced by context and include subjective biases [54]. An important step towards objective measurement of facial behavior was the development of the Facial Action Coding System (FACS) by Ekman and Friesen [54]. FACS categorizes micro facial movements into action units (AUs) that can be combined in various ways to produce a range of expressions. These AUs can be manually annotated within an image or a video using the FACS Coding manual [48], but this is an extremely time-consuming process for large-scale AU detection.

There has been significant work in the computer vision community focusing on automatically detecting both the abovementioned AUs themselves as well as the affective states denoted by combinations of these AUs (see [20, 101, 111] for detailed surveys). Although there is a widespread debate about the validity of inferring emotions from facial AUs, there is general consensus that facial movements contain useful information for social communication (see [49] and [15] for a thorough analysis). This has led to a large body of work on automatically detecting facial AUs from images and videos. For example, TAUD uses spatio-temporal local binary pattern descriptors to encode and classify upper facial AUs [75]. OpenFace 2.0 uses a linear support vector classifier and regressor to detect AUs and their intensities respectively, using histograms of oriented gradients as features [11]. Several commercially available facial affect classifiers also offer large-scale AU recognition capabilities (see [45] for a recent review). In addition to vision-based approaches, researchers have attempted to detect subsets of AUs or other well-defined face-engaged activities using other sensing modalities. Some approaches include using wearable devices for AU recognition using electromyography [112] and electrooculography [107].

Several approaches also exist for tracking eye gaze and head pose, of which computer vision-based techniques form the bulk. Fischer et al. propose a real-time gaze estimation system for natural settings [52]. Kim et al. collect a dataset and train neural network models for eye gaze estimation and pupil localization in near-eye images [76]. Mayberry et al. design an eyeglass wearable for real-time gaze monitoring [90]. These approaches show the feasibility of automatic and continuous AU, gaze, and pose detection in a non-intrusive manner.

2.3 Sensing Mental Health and Neural Activity

We now discuss efforts in the UbiComp community towards developing tools to sense various facets of the psychopathology of mental disorders, as well as the neural responses underlying these conditions.

There has been extensive prior work using smartphone data, such as phone usage, conversation patterns, location, and mobility, to detect mental illnesses. Smartphone data have been utilized to characterize depression [27, 109, 127], mood and anxiety disorders [67, 104], stress [86], bipolar disorder [2, 96], and schizophrenia [14, 126] among other psychopathological conditions. Additionally, a number of previous works utilize wearable sensors to support the diagnosis of mental health issues [110, 114, 124]. Several detailed reviews of smartphone- and wearable-based sensing of mental health outcomes are also available [1, 50, 95, 117]. Other approaches of inferring mental health outcomes include those based on social media engagement and web search patterns [38, 39, 72, 136],

vocal and speech patterns [97, 100], eye tracking [84, 132], social interactions [4] etc. There have also been attempts to use facial expressions and eye movement-related behaviors during specialized tasks or clinician interviews to diagnose mental disorders such as ADHD [82], schizophrenia [118], and autism [43] (see Table 1). In addition to the identification of mental disorders, there has also been work on designing effective interventions for the same [18, 87, 89, 102, 113, 129].

There has also been prior work on understanding emotion regulation processes and strategies. Bosse and de Lange propose a computational model of emotion regulation that would allow computational systems to estimate regulation capacities of human users [23]. Kou and Gui study emotions and emotion regulation strategies of players in online multiplayer games [79]. Harris and Nass study the emotion regulation processes of drivers in frustrated driving contexts [62]. There have also been extensive efforts to design and evaluate emotion regulation interventions. Costa et al. use false feedback of lower heart rate to help users regulate anxiety [35]. Yoon et al. describe various emotion regulation strategies that can be employed when designing interventions [135]. Azevedoo et al. describe how data visualizations can be used to support emotion regulation during self-regulated learning [9]. Fage proposes an application to support children with autism spectrum disorder in self-regulation of their emotions and to foster their inclusion in mainstream learning environments [51]. Ameko et al. propose a contextual bandit-based recommender algorithm for emotion regulation interventions [5]. However, most such studies have focused on adult populations and have mainly been concerned with understanding emotion and emotion regulation independent of their association with psychopathology. Our work focuses on emotion regulation early in life when these capabilities develop rapidly, and attempts to identify non-normative emotion regulation processes in order to quantify the psychopathological risk associated with it. We also focus on directly measuring the neural underpinnings of emotion regulation.

Perhaps most similar to our work with regard to measuring neural activation is that of Obuchi et al., who utilize mobile-sensing based behavioral features such as phone usage and conversation duration, sleep timings, location etc. to infer resting state functional connectivity between the ventromedial prefrontal cortex and the amygdala [98]. Lower resting state functional connectivity between these regions has been shown to be associated with pathological anxiety [77]. Earlier work from the same group also found correlations between smartphone usage patterns and the resting state functional connectivity between the subgenual cingulate cortex and the orbitofrontal cortex [68]. Both works utilize behavioral data collected from smartphones over a longitudinal period. Our work extends this field of research, focusing on inferring neural activation levels and screening for psychopathology based on short behavioral observations of about ten minutes.

Table 1 summarizes the novelty of EarlyScreen compared to previous work: we focus on predicting both neural activation *and* psychopathology in a preschool-aged population and achieve competitive prediction performance in this challenging context.

3 METHODOLOGY

3.1 Participants

Ninety-four participants, ages 3.5 to 5 years old (Mean age = 4.05, SD = .73%), participated in the present study (54.3% male, 45.7% female; 75% White, 9.8% Black or African American, 9.8% multiracial, 2.2% Asian, and 3.3% "choose not to respond"). Families were recruited through social media platforms and community outreach and completed a 5- to 10-minute phone screening to determine eligibility for participation. Exclusionary criteria included psychotic symptoms, an existing diagnosis of developmental or intellectual disabilities, a history of head trauma with loss of consciousness, and the inability to speak or understand English. One parent of the participant completed informed consent. The present procedure was part of a larger study assessing behavioral, neural, and physiological predictors of irritability and emotion regulation in young children. Families received a

Table 1. Comparison of EarlyScreen with previous works relating behavioral measurements to neural activation or psychopathology. We report the behavioral features used, target population, duration of observation/data collection, whether observation requires clinical involvement, and the resulting prediction performance (AUROC: area under the receiver operating characteristic curve, PFC: prefrontal cortex, FC: functional connectivity, AUs: action units, N/A: not applicable).

Work	Target	Behavioral Features	Participants	Duration	Clinician Involved?	Prediction AUROC
[58]	PFC activation	Facial expressions	65 (children aged 3-7)	<10 mins	N/A	N/A (linear association)
[98]	PFC-amygdala FC (high vs. low)	Smartphone Usage	75 (college students)	>14 days	x	0.81
[82]	ADHD	Gaze distribution	66 (adults)	≈18 mins	x	0.83
[118]	Schizophrenia	Facial AUs	67 (adults)	15 mins	✓	0.89
[43]	Autism	Gaze, voice, and facial expressions	81 (adults)	≈5 mins	x	0.84
EarlyScreen	PFC activation and emotion-regulation psychopathology	Facial expressions, head movement, eye gaze	76 (children aged 3-5)	<10 mins	x	0.85 and 0.80 respectively

$60 compensation for participating and children received a certificate and a small toy. This research study was approved by the Institutional Review Board of the University of Massachusetts Amherst.

3.2 Emotion Induction Task

Participants completed a computerized frustration-inducing task designed for preschool children titled "Incredible Cake Kids" [57] on a touch screen monitor while facial video and prefrontal cortex activation were recorded simultaneously (see Figure 2). The task premise was that a virtual bakery needs the child's help baking virtual cakes for different customers. Children were instructed to choose the "most delicious cake" for each customer. They were also told that some children are better than others at choosing the most delicious cake and that they would be evaluated on their performance. Before starting the task, the children watched an instructional video and practiced playing the game.

The children then completed 30 trials of the task. For each trial, a virtual customer appeared on the screen along with three virtual cakes for four seconds in which children picked the "most delicious" cake, followed by two seconds of anticipation, and two seconds of positive (e.g., happy) or negative (e.g., grumpy) feedback (see Figure 1). Unbeknownst to the child, virtual customers provided predetermined positive or negative feedback, which were organized into three negative (four negative and one positive trials grouped together) and three positive blocks (four positive and one negative trial), separated by 20-second rest periods between blocks. The task lasted approximately 10 minutes, and the entire session was video recorded for further analysis. On average, participants selected a cake in 25.77 (SD = 4.50) of the 30 trials, showing that the children were sufficiently engaged in the game.

3.3 Neural Activity via Functional Near-Infrared Spectroscopy (fNIRS)

Participants' neural activity was measured during the emotion induction task through non-invasive optical imaging via functional Near-Infrared Spectroscopy (fNIRS). In recent years, fNIRS has emerged as an alternative to traditional neuroimaging techniques such as EEG (which offers poor localization of brain activity) and fMRI.

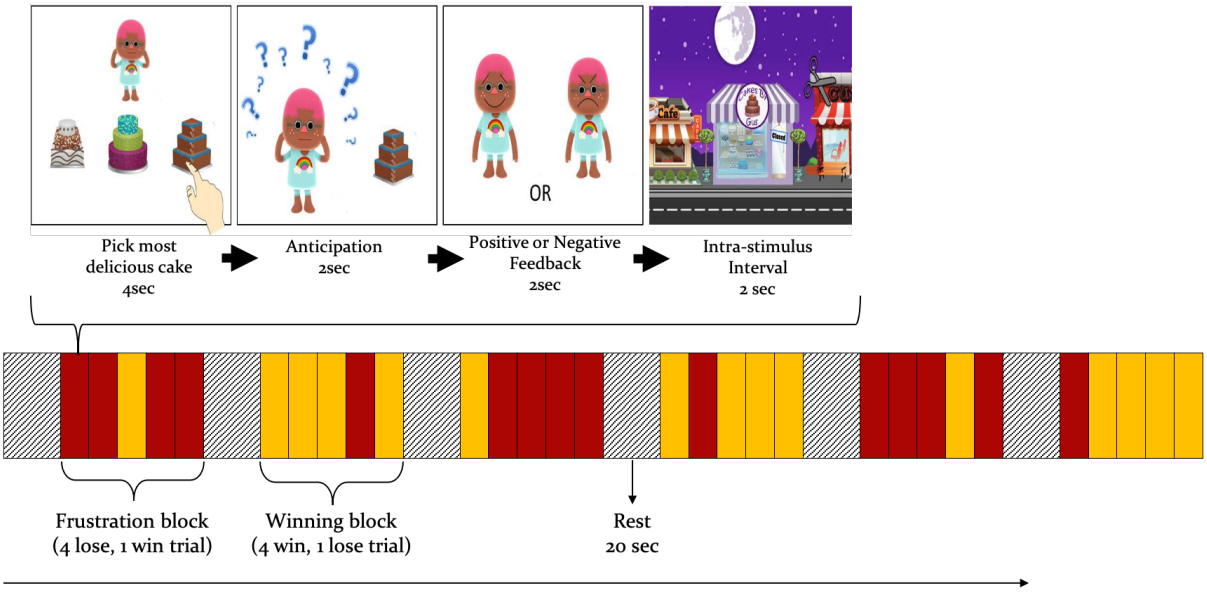


Fig. 1. Outline of the emotion induction task completed by the participants. The upper panel shows the design of the Incredible Cake Kids game, which is played 30 times (six blocks of 5 trials each). The lower panel shows the order of positive and negative trials.

Fig. 2. Experimental setup showing the child participant in the laboratory. The participant is positioned in front of a touchscreen computer screen and is wearing the fNIRS probe for neuroimaging.

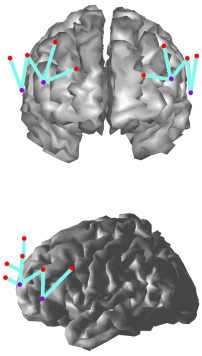


Fig. 3. Placement of the NIRS optodes on the prefrontal cortex. The red and purple dots show source and detector optode positions respectively, and the lines between them show measurement channels.

Compared to fMRI, fNIRS is better suited to measure neural activity in infants and children, as it is more robust to motion artifacts. Moreover, it allows the subject's face to be observed more clearly compared to fMRI, making it easier to record simultaneous brain and facial activity.

We used a NIRx NIRScout imaging system, with an fNIRS probe consisting of eight light-source emitters with 760nm and 850nm LED lights and four detectors. The sources and detectors were attached to an elastic cap with an average inter-optode distance of 3 cm. The international 10-20 coordinates [73] were followed to place the probe, aligning the interior medial corner of the probe with the prefrontal midline sagittal plane FpZ and extending it over Brodmann areas 10 (ventrolateral prefrontal cortex) and 46 (dorsolateral prefrontal cortex) on both the left and right hemisphere. The probe constituted 10 channels that were grouped into a single region of interest (ROI) – the lateral prefrontal cortex (LPFC) – similar to previous work (e.g., [58]). The ten measurement channels resulting from this placement are shown in Figure 3.

The fNIRS data was analyzed using the NIRS toolbox [1]. Data were recorded at 7.81 Hz and downsampled to 4 Hz for further analysis. The raw intensity per channel was used to calculate the delta optical density (ΔOD), or the change in light absorption through brain tissue over time. This is defined as

$$\Delta OD = -\log(I/I_0)$$

where I is the recorded signal intensity and I_0 is the reference baseline intensity. We then used ΔOD to calculate changes in oxyhemoglobin and deoxyhemoglobin (ΔHbO_2 and ΔHbR, respectively) using the modified Beer-Lambert law [71]. The change in oxyhemoglobin (ΔHbO_2) is modeled as a generalized linear model (GLM) for each experimental condition (Positive, Negative, and Rest blocks) per subject, where

$$\Delta HbO_2 = X * \beta + \epsilon$$

The design matrix X is given by a convolution of the stimulus timings with the canonical hemodynamic response function, which defines the shape of the expected change in ΔHbO_2 following a stimulus.

The GLM is fit using an autoregressive iteratively reweighted least squares approach, which corrects for motion artifacts and serially correlated errors due to underlying physiology [12]. We thus estimated the coefficients, β, for each channel during each condition. Finally, a single beta value is calculated by averaging the coefficients across all channels within the ROI per condition for each participant. The baseline beta for the Rest condition is subtracted from the values for the Positive and Negative conditions, giving us a measure of the magnitude of the relative evoked hemodynamic response for each condition. This serves as the ground truth measure of the level of neural activation during that block – a higher beta value indicates higher neural activity. In this work, we focus primarily on neural activity during frustration, that is, during negative blocks. Higher beta values during negative blocks indicate better emotion regulation, and low beta values signify poorer emotion regulation and greater risk of psychopathology [59].

3.4 Psychopathology Measures

In order to test our hypothesis of detecting diagnostic status from behavioral data, we also obtained participants' scores on a variety of clinically validated psychopathology measures.

First, caregivers reported their children's frequency of ADHD symptoms via the *ADHD Rating Scale-5 Home Version* [44]. The rating form consisted of a 4-point Likert scale (0 = Never or Rarely , 1 = Sometimes, 2 = Often, and 3 = Very Often), by which parents indicated the frequency of each behavior. Caregivers were instructed to select the number that best represented their child's behavior over the past six months. Following data collection, the 18 behavior items were subdivided into two subscales, ADHD Inattention (e.g., "Has difficulty sustaining attention") and ADHD Hyperactivity (e.g., "Has difficulty waiting his or her turn"). Children who scored 1-5 on these subscales were considered to be outside the clinical range for ADHD, and children who scored 6 or above were considered to be in the clinical range.

The Temper Loss subscale from the *Multidimensional Assessment Profile for Disruptive Behavior* (MAP-DB; [121]) was also used as a measure of child irritability. The MAP-DB aims to differentiate irritability in the normative

[1] https://github.com/huppertt/nirs-toolbox

range from irritability in the clinical range. The Temper Loss subscale specifically measures irritable mood (e.g., "Become frustrated easily") and tantrums (e.g., "Lose temper or have a tantrum during daily routines") as factors of irritability. Caregivers reported their child's irritability frequency over the past month via a 6-point Likert scale (1 = Never, 2 = Rarely (less than once per week), 3 = Some (1-3 days of the week), 4 = Most (4-6 days of the week), 5 = Every day of the week, and 6 = Many times each day). Children who received a total score of 42.5 or greater were considered to be in the clinical range.

Caregivers also reported their child's behaviors using the *Child Behavior Checklist* for ages 1.5 to 5 (CBCL; [3]). The CBCL comprised 99 items that were rated via a 3-point Likert scale (0 = Not True, 1 = Somewhat or Sometimes True, and 2 = Very True or Often True). Caregivers were instructed to select the number that best describes their child's behavior in the present or within the past two months. Items were subdivided into two subscales, Internalizing (i.e., symptoms related to anxiety and mood disorders) and Externalizing (i.e., symptoms related to disruptive behavior disorders and ADHD) behaviors. Children who scored a 65 or above in one or both of these subscales were considered to be in the clinical range.

Finally, we aggregated the scores of the participants on all scales to categorize them as within or outside the clinical range. Children were considered to be in the clinical range for psychopathological risk if they scored above the cut-off thresholds on *at least one of* the ADHD Inattention, ADHD Hyperactivity, CBCL Externalizing, or MAP-DB symptom scales. We do not consider the CBCL Internalizing Behavior subscale due to its poorer discriminatory power in children of our target age (internalizing disorders are also not prevalent at this age) [40]. Children scoring below the clinical threshold on all scales were considered to be in the non-clinical range overall. We later attempted to differentiate between clinical vs. non-clinical participants using behavioral features from videos.

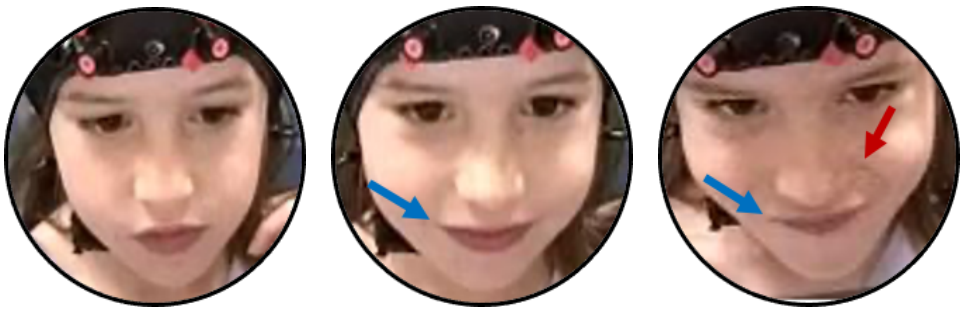
3.5 Behavioral Features Extracted from Videos

We used two high definition cameras – one trained on the child's face and the second one at an angle – to record children's facial expressions and head/upper body movement during the emotion regulation task. Based on observations from prior work, we extracted facial expressions, eye gaze, and head movement measures from the collected videos.

To extract visible facial expressions, we recorded facial movements using the Facial Actions Coding System (FACS) [54]. FACS allows visible facial expressions to be coded based on anatomical facial muscle movements categorized as Action Units (AUs). We used the OpenFace 2.0 library [10] for AU detection, which contains models to predict the presence or intensity of various AUs in images and videos. In this study, we extracted 18 facial AUs (see Appendix A) from the video stream obtained from the camera directly pointed toward the child's face. We disregard the camera placed at an angle since it fails to capture the entire face of the subject and sometimes also includes the experimenter in the frame. Since our study focuses on emotion regulation during frustration, we focused on facial expressions during and immediately following positive or negative feedback received by the children in each trial. We extracted 4-second-long video segments immediately after the feedback event, resulting in 30 segments (15 positive and 15 negative feedback) per participant.

From the same feedback segment videos, we also extracted the eye gaze direction and head pose per frame using OpenFace. The library computes a 3-dimensional gaze vector for each eye as well as an averaged gaze angle vector for both eyes in two dimensions. We used the latter measure to compute the change in gaze angle per unit time. To estimate head movement, we used OpenFace to calculate the position of the child's head within the frame relative to the (stationary) camera in 3D. We estimated the change in head position per unit time by computing the displacement between consecutive frames.

We also used the facial AUs to detect categories of facial expressions that have been shown to be relevant to emotion regulation [58]. The first category comprises negative expressions, characterized by the presence of one



(a) (b) (c)

Fig. 4. A child participant with (a) a neutral face, (b) a simple facial masking expression, and (c) a complex facial masking expression during negative feedback. The blue arrow shows contraction of the lip corner puller (AU 12) producing a smile. The red arrow shows contraction of the upper lip raiser (AU 10) producing a sneer, and deepening the nasolabial fold.

or more negative action units without the presence of any positive action unit. The second category consists of positive expressions which are considered to be exhibited when the child is *masking* their frustration – this is characterized by the presence of AU 12 (lip corner puller). Figure 4 shows a child demonstrating masking expressions of two kinds – simple masking, where AU 12 is not accompanied by any co-occurring negative AUs, and complex masking, where AU 12 is accompanied by the negative AU 10 (upper lip raiser). Both negative and positive (masking) expressions may be accompanied by eye constriction (AU 6). We grouped the relevant AUs extracted from OpenFace into positive/negative expressions with/without eye constriction in order to analyze their association with neural activation. See Appendix A for a list of all AUs extracted for the study, along with their categorization into positive and negative expressions.

4 MULTI-SCALE INSTANCE FUSION FRAMEWORK

As described in Section 1, EarlyScreen aims to utilize behavioral features extracted from videos to predict (i) neural activation levels in the PFC, as well as (ii) psychopathological disorder status among preschool children. The key challenge in doing so is the limited number of labels (one per individual) in our dataset, providing only coarse-grained subject-level information. At the same time, the frustration-inducing task completed by our participants comprises of multiple trials (as shown in Figure 1). This leads to the availability of up to 30 observations of each participant's behavioral response (15 positive and 15 negative feedback trials), which were recorded in the form of facial videos. Behavioral responses from each of these trials can be thought of as independent episodes of data containing fine-grained information.

In this paper, we propose a Multi-scale Instance Fusion (MIF) framework to bridge the gap between the availability of multiple independent behavioral observations and individual-level neural activation or psychopathology labels. The MIF framework harnesses both fine-grained information from each trial as well as coarse-grained information from the overall session to characterize an individual. It combines (i) a *Multiple Instance Learning (MIL) Pipeline* learning subject-level features from each instance of feedback with (ii) a corresponding *Single Instance Learning (SIL) Pipeline* operating on coarse-grained features extracted by aggregating all feedback segments. Figure 5 shows our proposed MIF architecture, which is an ensemble model consisting of these two components fused together in order to obtain the final predicted label. We now describe each component in the MIF framework in more detail.

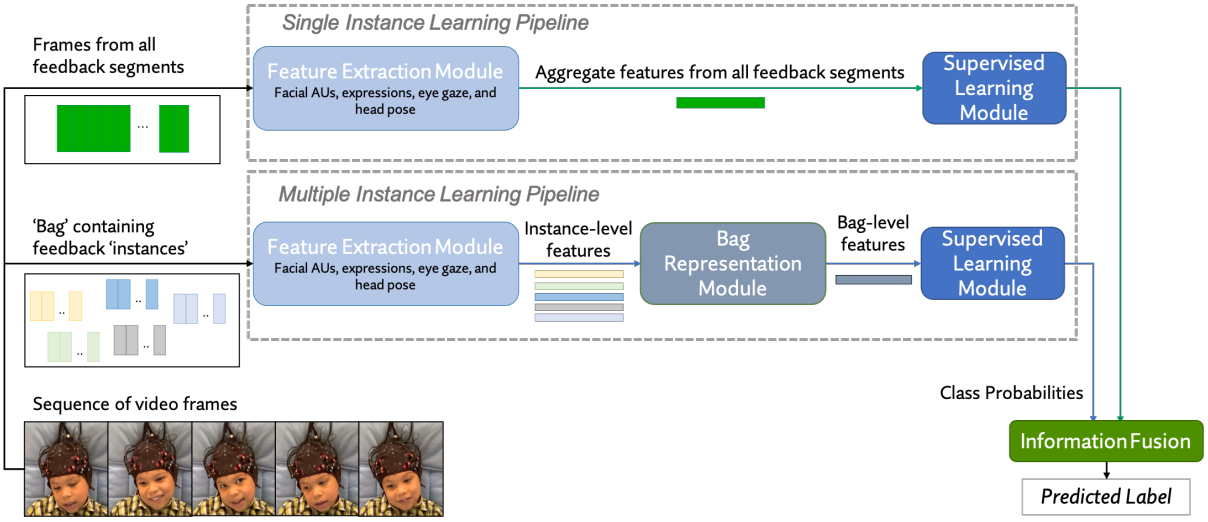


Fig. 5. The proposed Multi-scale Instance Fusion (MIF) framework. The MIF framework is an ensemble of two parallel classification pipelines operating on single and multiple instance features respectively. The predicted probabilities from both pipelines are fused to output the final class label.

4.1 Multiple Instance Learning Pipeline

Multiple Instance Learning (MIL) [42] is a weakly supervised machine learning framework where each sample in the dataset is a *bag* $\mathbf{B_i}$ with a single label Y_i. The bag contains n_i *instances* represented as $\mathbf{x_{ij}}$, $j = 1, 2, ..., n_i$, and the labels y_{ij} for individual instances are generally unavailable.

The MIL framework has been applied to a number of learning problems in prior literature, each with its own set of assumptions. The standard MIL assumption is defined as a classification problem in which negative and positive instances are grouped into bags such that negative bags contain only negative instances, whereas positive bags contain at least one positive instance [42]. Formally, the bag label Y_i can then be represented in terms of the instance labels y_{ij} as

$$Y_i = \begin{cases} +1 & \text{if } \exists y_{ij} : y_{ij} = +1 \\ -1 & \text{if } \forall y_{ij} : y_{ij} = -1 \end{cases}$$

In the above scenario, to classify a bag as positive, it is sufficient to identify one positive instance within the bag. On the other hand, the collective MIL assumption refers to problems where the bag label Y_i is defined by more than one instance label, or by none of the instance labels. Carbonneau et al. [28] provide a detailed review of MIL frameworks under different assumptions. Several approaches have been proposed to learn both bag- and instance-level labels under the MIL formulation. These include approaches that model instance labels as hidden variables [139], or extensions of regular supervised learning algorithms to an MIL space (e.g., [6, 138]).

The MIL framework can also be adapted and applied to problems that do not satisfy the standard assumption described above (e.g., [29, 130]). Some methods proposed for this setting include bag distance-based techniques [125], bag kernel representations [55], or bag dissimilarity mappings [116]. Another approach is to propagate instance-level features to a bag-level feature space and then utilize standard supervised learning techniques for the final classification [85].

The classification problems in our work can be translated to a *Multiple Instance Learning (MIL)* problem with relaxed assumptions where each individual is represented as a "bag" with a single label for neural activation levels or psychopathological disorder status. As described earlier, our task contains 30 trials - 15 positive and 15 negative feedback - grouped into six blocks. Each of these trials can be thought of as an "instance" within the bag. A feature extraction module extracts instance-level features, which in our case include facial AUs, expressions, eye gaze, and head pose. These instance-level features are collectively used to compute a bag representation, and a supervised learning module uses this representation to predict class probabilities. This makes up what we define as a *Multiple Instance Learning (MIL) pipeline*.

4.2 Single Instance Learning Pipeline

While the MIL setup described above allows us to utilize each observed positive/negative feedback instance on its own, it fails to capture overall behavioral characteristics from the participant's multiple trials. This is in turn achieved by the *Single Instance Learning (SIL) Pipeline*, which uses coarse-grained features from facial video frames belonging to all feedback segments in the frustration inducing task. These features are extracted by a feature extraction module and act as inputs to a supervised learning module that outputs predicted probabilities for each class. The predicted probabilities from both SIL and MIL pipelines are fused together by weighted averaging, resulting in a final probability assigned to each class that is used to determine the predicted label.

4.3 Feature Extraction Module

The feature extraction module is part of both the SIL and MIL pipelines in the MIF framework. Features computed over all feedback segments are passed to the supervised learning module in the SIL pipeline, whereas features are computed for each instance separately and passed to the bag representation module in the MIL setting. More specifically, the feature extraction module within the SIL pipeline generates a single representation for all data segments associated with a negative or positive feedback segment. In the MIL pipeline, features are extracted separately from each distinct 4-second feedback segment.

Given a set of video frames, the feature extraction module first utilizes the OpenFace library to compute frame-level presence of facial AUs, head pose, and gaze direction. We then identify the presence of each predefined facial expression (positive/negative expressions with eye constriction, positive/negative expressions without eye constriction, and all positive/negative expressions) in each frame. We consider six different feature sets that are extracted by the Feature Extraction Module:

- **AU:** Includes the presence (present / absent), duration (fraction of time present), and average intensity of each AU extracted from OpenFace (see Table 6) within a given segment.
- **Movement:** Includes mean shift in eye gaze per unit time, standard deviation of the shift in eye gaze per unit time, mean shift in head pose per unit time, and standard deviation of the shift in head pose per unit time within a given segment.
- **Facial Expressions:** Includes duration of positive expressions (with eye constriction, without eye constriction, total) and negative expressions (with eye constriction, without eye constriction, total) within a segment (see Section 3.5).
- **AU + Movement:** Combination of the AU and Movement feature sets.
- **AU + Facial Expressions:** Combination of the AU and Facial Expressions feature sets.
- **AU + Movement + Facial Expressions:** Combination of the AU, Movement, and Facial Expressions feature sets.

4.4 Bag Representation Module

The bag representation module within the MIL pipeline is responsible for learning a mapping from a bag's representation $\mathbf{B_i}$ in the instance-level feature space to a bag-level representation $\mathbf{B_i^\phi}$. The choice of mapping depends on a number of key considerations. In the context of our work, these include the following:

(1) The label space for the bags and the label space for the instances are different. In our application scenario, the bag labels are assigned based on the individuals' observed neural activation over the entire task or based on the psychopathology symptom scores from questionnaires. On the other hand, instances within a bag correspond to different trials of the same participant and therefore do not have a neural activation or psychopathology label of their own. Given this distinction, our MIL pipeline should be applicable irrespective of whether a relationship exists between the bag and instance label spaces, making our framework more general than the standard MIL formulation.
(2) For simplicity, we assume that the instances in a bag are not temporally ordered, i.e., each trial is independent of the others and the order of trials is not relevant. Therefore, our instance-to-bag mapping should be permutation invariant.
(3) The number of observed trials for each participant can be different. Missing trials can occur if a child does not select a cake and therefore does not receive feedback in a trial, or if their face is occluded from the camera and we are unable to capture data. Therefore, there should be no constraints on the number of instances in each bag.

We evaluated a number of bag representation functions from MIL literature based on these considerations, and selected a subset of choices satisfying the above criteria. These mapping functions are listed below (see Appendix B for mathematical definitions):

- **Mean Mapping:** aggregation of features by averaging across instances.
- **Minimax Mapping:** representation using minimum and maximum values of each feature across instances.
- **Polynomial Minimax Kernel** [55]: representation of bag similarities as a polynomial kernel based on Minimax mapping.
- **MInD Mapping** [30]: representation using a vector of bag-to-bag dissimilarities.
- **CCE Mapping** [140]: bag representation based on instance-level clustering.
- **MILES Mapping** [29]: representation using a vector of bag-to-instance similarities.
- **Discriminative Bag Mapping (aMILGDM)** [133]: representation using a vector of similarities between each bag and each instance in a discriminative instance pool.

The above mapping algorithms are a non-exhaustive list of choices that can be utilized as part of the bag representation module in the MIF framework. They can be substituted by other algorithms that result in the transformation of a bag $\mathbf{B_i}$ containing $\mathbf{x_{ij}} \subseteq \mathbb{R}^d$, $j = 1, 2, ..., n_i$ into a representation $\mathbf{B_i^\phi}$ in the bag feature space. The resulting bag representation $\mathbf{B_i^\phi}$ is used as input to a supervised learning module as shown in Fig. 5. We later discuss the effectiveness of more complex bag representations over baselines such as Mean and Minimax mapping in Section 7.1.

4.5 Supervised Learning Module

Both the SIL and MIL pipelines in the MIF framework contain a supervised learning module, the primary component of which is a standard supervised machine learning classifier. We limit the choice of classifiers to probabilistic classifiers that predict a conditional distribution $\Pr(Y = y|X)$ for each class y. In addition to a classifier, the module may contain submodules for preprocessing input features (either coarse-grained features in the SIL pipeline or the bag representations in the MIL pipeline), including standardization or normalization, feature selection, under- and over-sampling to deal with class imbalance, etc.

4.6 Information Fusion and Prediction

The final component of the MIF framework is the information fusion module that takes as inputs the predicted class probabilities from the SIL and MIL pipelines and aggregates them by weighted averaging to output a final probability. Specifically, the final conditional probabilities are calculated as

$$\Pr(Y = y|X) = \lambda * \{\Pr(Y = y|X)\}_{SIL} + (1 - \lambda) * \{\Pr(Y = y|X)\}_{MIL}$$

The predicted label is then calculated based on this aggregate probability:

$$\hat{y} = \arg\max_{y} \Pr(Y = y|X)$$

The weighted fusion proposed above ensures that our MIF framework performs at least as well as the SIL pipeline alone (when $\lambda = 1$) or the MIL pipeline alone (when $\lambda = 0$). We hypothesize that the fusion of the two would improve classification performance by learning both inter-instance and inter-bag variability. As a result, the value of the hyperparameter λ can be interpreted as being proportional to the importance of coarse-grained, single-instance features and inversely proportional to the importance of the instance-level features in the classification problem. We later demonstrate that setting $\lambda = 0$ or $\lambda = 1$ leads to suboptimal performance, and a value of λ between 0 and 1 gives optimal fusion (see Section 7.2).

5 PREDICTING HIGH VS LOW PFC ACTIVATION DURING FRUSTRATION

We now turn to using our MIF framework to classify individuals with normal vs. low Pre-Frontal Cortex (PFC) neural activation associated with emotion regulation during frustration. Although we collected data from 94 participants, some participants had to be excluded due to technical issues in fNIRS recording ($N = 13$), missing video data ($N = 1$), or missing stimulus recordings to synchronize fNIRS readings with videos ($N = 4$), and we could only use data from 76 participants.

As described in Section 3.3, we extracted ground truth beta values from the fNIRS recordings, which indicate the magnitude of the hemodynamic response during the Negative block as compared to the baseline Rest period. A low beta value is indicative of lower emotion regulation-related neural activity in response to frustration, which is tied to greater psychopathological risk. To split individuals into two groups – individuals with "Normal" vs. "Low" activation levels – we used one standard deviation below the mean activation level across all subjects (mean-1SD) as the threshold, which is a standard practice for psychiatric evaluation (e.g., [59]). This categorization led to 12 individuals classified as exhibiting low activation and 64 individuals with normal levels of activation.

Since our focus is on predicting neural activation during frustration, all features (as described in section 4.3) were first calculated from the negative feedback segments of the frustration-inducing task. We then calculated the difference between each feature for the negative and positive segments, obtaining twice the number of features we originally had. For the MIL pipeline, each negative feedback segment was considered a separate "instance". Along with the features extracted from the instance itself, we again calculated the difference between the instance features and the average of each feature across positive feedback segments.

5.1 Baseline Single Instance Learning (SIL) Models

To evaluate the effectiveness of our proposed MIF framework, we first trained baseline SIL models using each of the feature sets described in Section 4.3. We trained and evaluated nine different machine learning models (listed in Appendix C, Table 7) to predict activation levels. Please refer to Appendix C for more details on pre-processing, feature selection, and addressing class imbalance.

We used a nested cross-validation scheme to select the best hyperparameters for each supervised machine learning algorithm and evaluate the pipeline's generalization performance. We used an outer 5-fold cross-validation scheme that assigns a fifth of all subjects to the test set at each fold, training the model on the

Table 2. Classification performance for low vs. normal activation detection using baseline Single Instance Learning (SIL) pipelines and the proposed Multi-scale Instance Fusion (MIF) model.

Framework	Feature set	Best Model	Area under ROC curve
SIL	**AU**	**Random Forest**	**0.80**
	Movement	Gradient Boosting	0.54
	Facial Expressions	Gradient Boosting	0.57
	AU + Movement	AdaBoost	0.59
	AU + Facial Expressions	AdaBoost	0.59
	AU + Movement + Facial Expressions	Logistic Regression	0.58
MIF	**AU**	**Polynomial Minimax Kernel with Random Forest**	**0.85**

remaining subjects. The test set at each fold is stratified, i.e., each test set contains the same proportion of subjects with normal and low activation. Each subject is only assigned to the test set once. Within the training set at each fold, we applied stratified 3-fold cross-validation to select optimal model hyperparameters. The hyperparameter choices for each algorithm are listed in Table 7. The best performing model in this inner cross-validation loop was evaluated using the test set from the outer fold to obtain an unbiased estimate of classification performance.

The best performing SIL algorithm on the outer test sets for each feature set is listed in Table 2. We find that the AU feature set with a random forest classifier as the supervised learning approach performs best, resulting in an area under the ROC curve (ROC AUC) of 0.80. The importance of AU features in predicting neural activation levels is also supported by previous work in cognitive neuroscience (e.g., intensity of a frowning action has been linked to neural activity in the amygdala and the PFC [64]). It is also interesting to note that logical combinations of AUs into facial expressions have lower predictive power, although these combinations have been found to correlate with neural activity [58]. We hypothesize that the AU feature set contains richer information, since it also includes action units that are not accounted for in the expression combinations (see Appendix A).

5.2 Comparing Multi-scale Instance Fusion Models with SIL Baseline

We further trained and evaluated our proposed Multi-scale Instance Fusion (MIF) framework to classify low vs. normal activation levels. We used the same nested cross-validation scheme detailed above. MIF models were trained using the AU feature set, which resulted in the best performance classifying neural activation in the SIL setting. As part of the bag representation module, we evaluated the seven mapping algorithms discussed in Section 4.4. As shown in Table 2, we found that an MIF model that uses AU features with a Polynomial Minimax Kernel representation achieves the best overall area under ROC curve of 0.85 in classifying PFC activation – a significant improvement over the baseline models. This supports our hypothesis that the MIF framework can improve performance by taking into account instance-level features. We also found that trivial feature aggregation through mean and minimax mappings does not lead to an improvement in performance (ROC AUC = 0.80, same as SIL model), demonstrating the utility of formulating the classification as an MIL problem and computing discriminative features at the bag level.

The ROC curve of our MIF model is shown in Figure 6. The model performance across 5-fold cross validation gave an average area under ROC curve of 0.82 (SD = 0.14), suggesting generalizability of the proposed model. We then used the ROC curve to select a probability threshold for classification where the sensitivity and specificity of the model are most balanced (i.e. the threshold minimizing the |sensitivity − specificity| metric). This point is shown in Figure 6 – our model achieves a sensitivity of 0.75 and a specificity of 0.77 at the chosen threshold. The

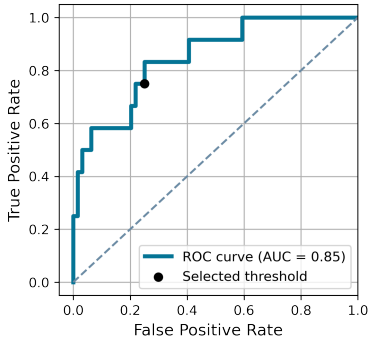
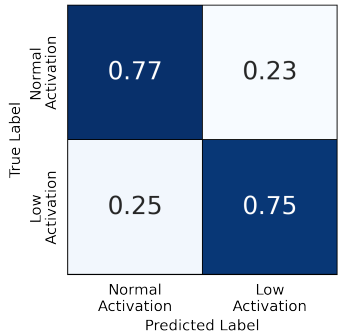


Fig. 6. The receiver operating characteristic (ROC) curve of the best performing model for predicting PFC activation. The area under the ROC curve is 0.85.



Sensitivity/Recall	0.75
Specificity	0.77
Precision	0.77
F1 Score	0.76

Fig. 7. Normalized confusion matrix showing classification results of the best performing model for predicting PFC activation.

normalized confusion matrix showing the fraction of correctly classified individuals in each class is shown in Figure 7. Note that the threshold can be adjusted to optimize for either of these metrics at the cost of the other – in practice, this decision can be made by experts based on the costs of misidentifying subjects with low and normal activation respectively.

These highly promising results demonstrate the possibility of utilizing EarlyScreen to classify the magnitude of PFC neural activation during frustration using behavioral data. To the best of our knowledge, our work is the first to attempt predicting an objective measure of emotion regulation and to produce proof-of-concept results. Current tools to screen for emotion regulation disorders often depend on symptomatic reports from parents and caregivers, which have been shown to have modest prediction performance. For example, the Child Behaviour Checklist (CBCL) was found to demonstrate a mean sensitivity of 0.66 and specificity of 0.83, while the Strengths and Difficulties Questionnaire (SDQ) achieved a mean sensitivity of 0.49 and specificity of 0.93 [128]. Our model is able to achieve sensitivity and specificity levels comparable to these screening tools with less than ten minutes of facial observations that can be collected remotely at home while completing a clinically validated task.

6 PREDICTING PSYCHOPATHOLOGY DIAGNOSIS FROM BEHAVIORAL FEATURES

In addition to identifying objective neural activation levels, we attempted to use automatically extracted facial expressions and movement information to classify the clinical diagnosis status of individuals. As ground truth, we used the children's scores on the CBCL Externalizing subscale, ADHD Inattention and Hyperactivity subscales, and MAP-DB scale as described in Section 3.4 to categorize them into those below or above the clinical threshold. Among the 76 children in our study, 25 scored above the threshold on at least one of these scales and were categorized as 'Clinical' participants. The other 51 were classified as 'Non-clinical' participants, indicating a low risk of psychopathology.

6.1 Baseline Single Instance Learning (SIL) Models

Similar to our pipeline for classifying activation levels, we used a nested cross-validation approach to first train and evaluate baseline SIL models, using the same candidate feature sets described in Section 4.3. Table 3 shows the results of our analysis – we found that an AdaBoost classifier using AU + Movement + Facial Expressions features achieves the best classification performance with an ROC AUC of 0.77.

Table 3. Classification performance for detecting clinical vs. non-clinical participants using baseline Single Instance Learning (SIL) pipelines and the proposed Multi-scale Instance Fusion (MIF) model.

Framework	Feature set	Best Model	Area under ROC curve
SIL	AU	Gradient boosting	0.52
	Movement	Random forest	0.72
	Facial Expressions	SVM with RBF kernel	0.51
	AU + Movement	Random forest	0.72
	AU + Facial Expressions	KNN	0.57
	AU + Movement + Facial Expressions	**AdaBoost**	**0.77**
MIF	**AU + Movement + Facial Expressions**	**MInD Mapping with AdaBoost**	**0.80**

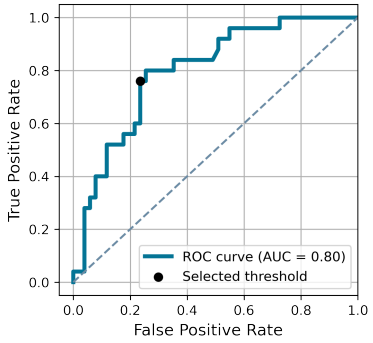


Fig. 8. The receiver operating characteristic (ROC) curve of the best performing model for predicting clinical disorder status. The area under the ROC curve is 0.80.

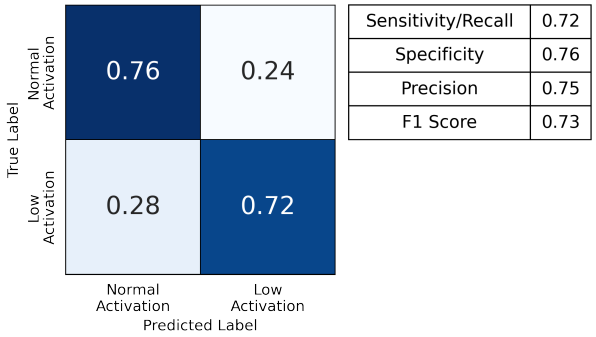


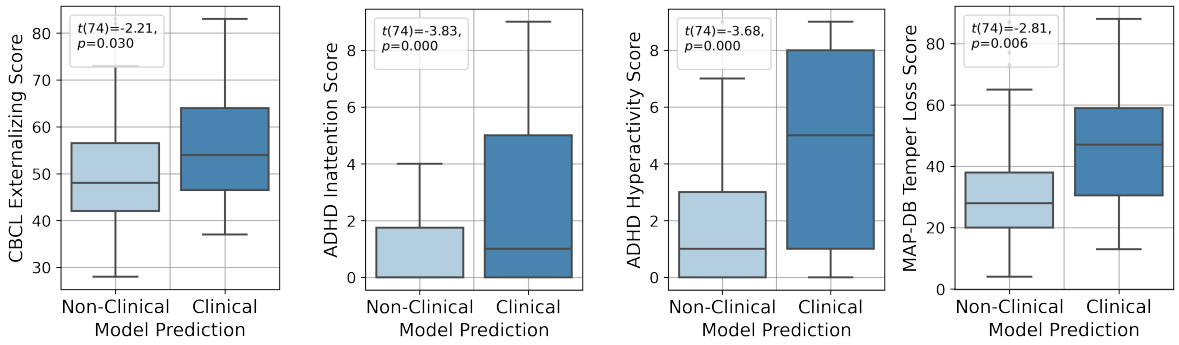
Fig. 9. Normalized confusion matrix showing classification results of the best performing model for predicting clinical disorder status.

From Table 3, we see that Movement features outperform both AU and Facial Expressions separately at predicting clinical scores. Prior work has also shown associations between eye and body movements and scores on psychopathological scales. Children with higher scores on the CBCL and other diagnostic scales have been found to exhibit higher bodily movements [7], and studies have identified differences in eye movements and gaze patterns among ADHD and control subjects [83]. We found that the addition of AU and Facial Expressions to the Movement feature set resulted in further improvement in classification performance, which is supported by prior work on facial expressions [41].

6.2 Comparing Multi-scale Instance Fusion Models with SIL Baseline

We then investigated whether our proposed MIF framework improves classification performance by combining information from representations of instance-level features. Similar to the procedure described for classifying neural activation, we trained MIF models using the AU + Movement + Facial Expressions feature set and an AdaBoost classifier within the supervised learning module.

We found that an MIF model with MInD bag representation achieved the best overall area under ROC curve of 0.80 using AU + Movement + Facial Expressions, compared to an AUC of 0.77 in the baseline SIL setting. Similar



(a) CBCL Externalizing (b) ADHD Inattention (c) ADHD Hyperactivity (d) MAP-DB Temper Loss

Fig. 10. Distribution of scores on various symptom scales for each predicted class. All t-tests are significant after correcting for false discovery rate using the Benjamini-Hochberg procedure at significance level $\alpha = 0.05$.

Table 4. Correlation between predicted probability of being classified as 'Clinical' and scores on different psychopathological symptom scales. Higher scores indicate abnormality on all scales. The table shows p values that are not corrected for multiple comparisons, and * indicates significance after correcting for the false discovery rate using the Benjamini-Hochberg procedure at significance level $\alpha = 0.05$.

	Pearson r	p value
CBCL Externalizing	0.35	0.002*
ADHD Inattention	0.42	0.0004*
ADHD Hyperactivity	0.41	0.0003*
MAP-DB Temper Loss	0.38	0.001*

to neural activation classification, we found that MInD mapping, which accounts for dissimilarities between bags, improves performance, whereas statistical aggregation methods do not. The mean test area under ROC curve of our best performing model over 5 folds was 0.79 (SD = 0.05). We then selected a threshold for classification based on the ROC curve to minimize the |sensitivity − specificity| metric. This point is shown in Figure 8 – the model achieves a sensitivity of 0.72 and a specificity of 0.76 at this threshold. The normalized confusion matrix depicting the performance of the classifier is shown in Figure 9.

The performance of our model is comparable to recent approaches that predict clinical symptoms using behavioral data. For instance, Place et al. predict depressive mood using mobile sensing with an area under ROC curve of 0.74 [104]. Mock et al. classify individuals scoring high vs. low (top and bottom third of scores - not clinical vs. non-clinical risk status) on ADHD inattention and hyperactivity subscales with an accuracy of 81.1% and 88.9% using touch interaction features [94]. Our approach performs reasonably well at the difficult problem of categorizing psychopathological risk status in preschool-aged children using a short and unobtrusive behavioral screening tool. This supports the applicability of EarlyScreen as a screening procedure for emotion regulation-related psychopathological disorders in the wild.

6.3 Association between Model Predictions and Psychometric Scores

To further test the validity of our psychopathology classification model, we compared the distribution of reference or ground truth scores on the CBCL Externalizing Behavior, ADHD Inattention, ADHD Hyperactivity, and MAP-DB Temper Loss subscales among the individuals predicted to be Clinical and Non-Clinical. Figure 10 shows the distribution of the scores for each predicted class. The mean scores of the subjects predicted to be Clinical were significantly higher than those of the subjects predicted to be Non-Clinical on all psychometric scales ($p < 0.05$).

We also examined the association between the model's predicted probability of classifying an individual as Clinical and their scores on the psychopathology scales (see Table 4). We found a statistically significant positive correlation between predicted probability of being above Clinical threshold and the participants' score on each psychometric subscale ($p < 0.01$ for all subscales). Since our analysis involves multiple comparisons, we used the Benjamini-Hochberg procedure [19] to control for the false discovery rate (FDR) at significance level $\alpha = 0.05$. All t-tests and correlations reported above remain significant after FDR adjustment. Overall, our analysis indicates that the predictive model is consistent with real-world diagnostic tools at identifying individuals with significant psychopathological risk.

7 OPTIMAL BAG REPRESENTATION AND INFORMATION FUSION

7.1 Bag Representation

As part of our analysis, we also evaluated two statistical feature aggregation methods – Mean and Minimax mapping – as baselines for the Bag Representation Module (see Section 4.4) in the MIF framework. Notably, we found no improvement using these statistical aggregates as the bag representations in either classification problem. In both cases, the MIF models with Mean and Minimax representation achieved the same ROC AUC as the SIL baselines, underscoring the ineffectiveness of aggregation-based bag representations.

We instead found that the Polynomial Minimax Kernel representation outperformed other approaches in classifying neural activation levels, while MInD mapping achieved the highest ROC AUC in classifying psychopathological disorder status. Both these bag representation algorithms account for overall bag-to-bag similarities, as opposed to other MIL mappings which compute bag-to-instance similarities. This suggests that inter-individual differences in emotion regulation responses outweigh differences between trial-level responses across participants.

7.2 Information Fusion

As discussed in Section 4.6, the information fusion approach in the MIF framework guarantees that the MIF model will perform at least as well as the best SIL and MIL pipelines that constitute it. The results in Sections 5.2 and 6.2 indicate that there is a significant improvement in classification performance for both neural activation and psychopathology detection when the SIL pipeline is augmented as proposed in our framework.

Figure 11 shows the performance of the proposed MIF model for predicting neural activation using different values of λ for information fusion. As described in Section 4.6, $\lambda = 0$ corresponds to using only the MIL pipeline for predictions, while setting $\lambda = 1$ leads to using only the SIL pipeline. Any value of λ between 0 and 1 is a fusion of both pipelines. We observed that setting $\lambda = 0.6$ achieves the best classification performance (mean= 0.87, SD=0.09) for neural activation prediction. Figure 12 shows the average ROC AUC for different values of λ for the MIF model to predict clinical disorder status. The best performing model achieved a mean AUC of 0.79 (SD = 0.06) at $\lambda = 0.4$. We found that a fusion architecture performed better than both a standalone SIL pipeline and a standalone MIL pipeline. This is true for both our neural activation and clinical status prediction models, and underscores the utility of combining multi-scale feature representations for such prediction problems.

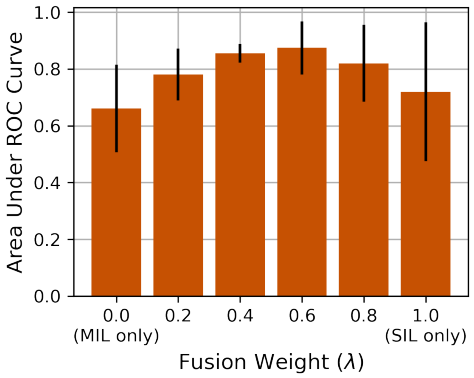


Fig. 11. Average area under ROC curve over 5 folds for different values of λ in the best performing MIF model for predicting neural activation levels.

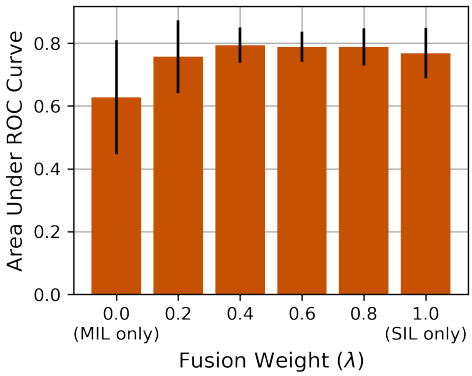


Fig. 12. Average area under ROC curve over 5 folds for different values of λ in the best performing MIF model for predicting clinical disorder status.

8 DEPLOYMENT CONSIDERATIONS

8.1 Fairness and Ethical Considerations

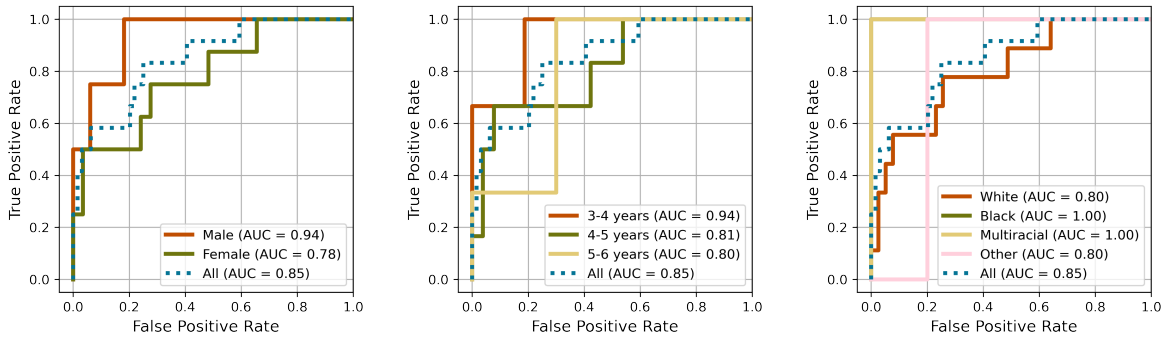
We now discuss ethical considerations related to deploying EarlyScreen's neural activation or psychopathology classifiers in the real world. We ground this discussion in the model reporting criteria proposed by Mitchell et al. [93], providing a comprehensive review of the intended use, relevant factors, and metrics related to our models.

8.1.1 Ethical Considerations: As described in Section 1, a primary aim of our work was to investigate whether facial expressions and movement-related behavioral data automatically extracted from facial videos can be utilized to predict coarse-grained neural activation during frustration. In doing so, we used facial AUs extracted using computer vision algorithms and leveraged their known association with neural activity [58]. It is important to note that we do not attempt to predict *emotion* using these facial AUs – there is significant debate about the validity of using facial movements to infer emotions (see [15]). The use of gamified tasks to induce frustration has also been validated previously [59].

Additionally, since our model uses data extracted from video recordings of children's faces, it is important to consider the privacy implications of collecting and processing this data in a real-world deployment. This is especially important since our models act as mental health screening tools, whose outcomes might lead to undue stress or stigmatization if not handled correctly [63]. To minimize unintended harms and biases, the models do not use any demographic data or protected information to make predictions.

8.1.2 Intended use: As part of EarlyScreen, we present two MIF models trained on facial AUs and movement-related features that are each intended to be used for the following purposes, respectively:

(1) As a screening tool for identifying preschool-aged children who may exhibit low neural activation during frustration, a risk factor for broad psychopathology.
(2) As a screening tool for identifying preschool-aged children who fall above the clinical threshold for specific disorders common in early childhood.



(a) ROC curves by gender (b) ROC curves by age (c) ROC curves by race

Fig. 13. Performance of the neural activation classification model by demographic group.

The proposed models are intended to be used as screening tools that could assist a childhood mental health practitioner in making a rapid and accurate diagnosis. In addition, the models are *not* meant to be used to detect faces or facial characteristics, or infer felt emotions or personal characteristics of users.

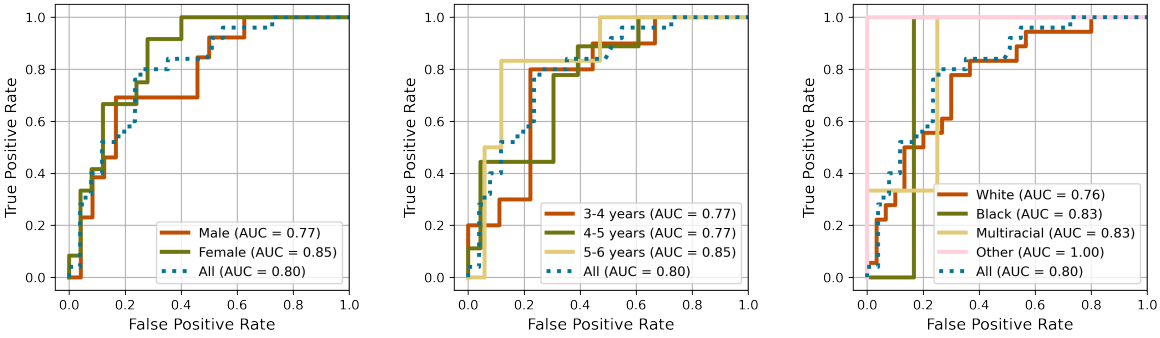
8.1.3 Factors Affecting Model Performance: As with other human-centered computer vision technology, our models' performance is likely to be impacted by several factors related to participants' identity and personal characteristics such as gender, age, race and ethnicity, Fitzpatrick skin type [53] etc. It might also be affected by complex interactions of these features, as well as external factors such as camera hardware and placement, lighting, other environmental factors, etc. Note that this is in addition to individual differences in emotion regulation itself, which may be influenced by factors outside the purview of this work.

We present quantitative analysis of the performance of our prediction models disaggregated by the demographic factors available in our dataset, i.e., gender, age group, and race. For a breakdown of our subject population as well as the number and percentage of participants with low neural activation or clinical symptoms in each demographic subgroup, please refer to Appendix D. We examine model performance with respect to each unitary factor.

We first evaluate the performance of our neural activation prediction model by demographic group. Figure 13 shows the ROC curves for each subgroup split by gender, age, and race along with the overall ROC curve. We find that the model achieves a higher ROC AUC for males (0.94) than for females (0.78). The model performance is also higher among younger participants – the AUC for 3 to 4-year-olds is 0.94 while that for ages 4-5 and 5-6 are 0.81 and 0.80 respectively. Disaggregating by racial groups, we see that the model achieves an AUC of 1.0 for Black and Multiracial participants and an AUC of 0.80 among participants self-identifying as White or Other racial group.

Separating demographic subgroups and evaluating the performance of our clinical psychopathology classification model, we find that the ROC AUC for male participants is 0.77 and that for female participants is 0.85 (see Figure 14). Across age groups, we see that the model achieves an ROC AUC of 0.77 among ages 3-4 and 4-5, while the performance among 5- to 6-year-olds is slightly higher at 0.85. We also observe that the model exhibits an ROC AUC of 0.76 among White participants, 0.83 among Black as well as among multiracial participants, and 1.0 among participants from Other racial groups.

The above analysis shows that our models achieve reasonable performance across different demographic subgroups. Although the performance of the model varies with the number of participants in each subgroup



(a) ROC curves by gender (b) ROC curves by age (c) ROC curves by race

Fig. 14. Performance of the psychopathology classification model by demographic group.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
As a field, we need to improve the accuracy, efficiency, and convenience of how we diagnose early childhood mental illness.	1	0	1	11	41
I am satisfied with current practices using questionnaires, interviews, and observations to make mental health diagnoses.	6	15	6	22	5
A patient's biological data could someday improve the accuracy of their diagnosis.	0	2	11	31	9
Inexpensive and widely available neuroimaging data could someday improve diagnostic accuracy.	3	5	15	19	11
Continuous behavioral data collected in home settings could someday improve diagnostic accuracy.	1	1	5	24	23
Low-income, low-resource families need additional support to make attending weekly assessment/therapy sessions less burdensome.	2	0	2	15	35
It is important for diagnostic intakes to occur only at the clinic.	13	25	11	3	1
Surveys/clinical questionnaires filled by parents or caregivers are an integral part of the diagnostic process.	0	0	2	10	41
Home-based diagnostic tools could make accessing clinical services more convenient for some families.	1	2	5	23	22
Surveys/clinical questionnaires administered multiple times over a period of time could be helpful for tracking clinical progress.	1	0	1	21	31

Fig. 15. Survey respondents' attitudes towards current diagnostic practices and beliefs about the potential utility of other sources of data.

and the base rate of abnormalities in the subgroups, the relative consistency of the results is encouraging for the deployment of these models in the real world. Further research should validate their performance in broader populations.

8.2 Utility for Practitioners

To evaluate the usability, utility, and drawbacks of EarlyScreen from a clinical perspective, we conducted a user survey of mental health professionals who were introduced to this technology and asked for feedback that

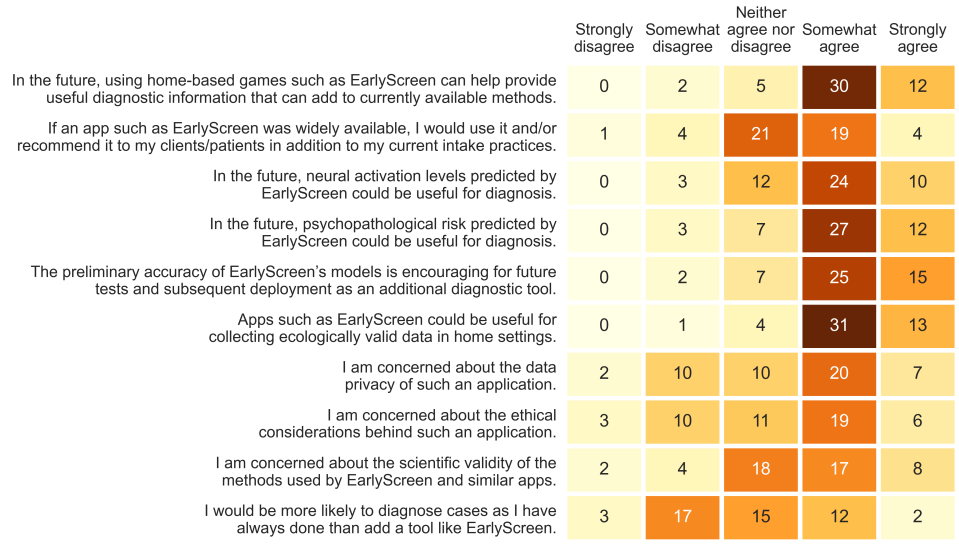


Fig. 16. Survey respondents' feedback on the utility of EarlyScreen and potential concerns for deployment.

could be incorporated into future versions. Practitioners were recruited through the American Psychological Association's mailing list for the Society of Clinical Child and Adolescent Psychology and were offered a $5 gift card for their participation. A total of 60 respondents completed the survey, of which 11 completed it partially. We present preliminary findings from this survey to illustrate how EarlyScreen can support current clinical practices.

8.2.1 Need for Home-Based Diagnostic Tools and Novel Data Sources: Participants were first asked about their current clinical practices, their satisfaction with existing diagnostic measures, and any additional sources of diagnostic information they would like to access. They were not introduced to this research or EarlyScreen at this stage to obtain unbiased responses about their actual clinical needs and attitudes about at-home care. Figure 15 shows the number of respondents who rated each statement between 1 ("Strongly disagree") and 5 ("Strongly agree"). An overwhelming majority of respondents strongly agreed ($N = 41$ or 75.9%) or somewhat agreed ($N = 11$ or 20.4%) that *As a field, we need to improve the accuracy, efficiency, and convenience of how we diagnose early childhood mental illness.* Most of the respondents felt that patients' *biological* ($N = 40$ or 75.5%), *behavioral* ($N = 47$ or 87%), and *neuroimaging data* ($N = 30$ or 56.6%) could someday improve diagnostic accuracy, and that *questionnaires filled by parents or caregivers are an integral part of the diagnostic process* ($N = 51$ or 96.2%). These responses indicate the potential clinical utility of both the behavioral videos and the subsequent metrics predicted by EarlyScreen.

Clinicians also showed positive attitudes towards at-home screening, with 38 respondents (71.7%) disagreeing with the idea that *it is important for diagnostic intakes to occur only at the clinic.* Nearly all respondents ($N = 50$ or 92.6%) also felt that *low-income, low-resource families need additional support to make attending weekly assessment/therapy sessions less burdensome*, and that *home-based diagnostic tools could make accessing clinical services more convenient for some families* ($N = 45$ or 84.9%). EarlyScreen is a step towards realizing this vision of convenient, at-home mental health screening through accessible mobile applications.

8.2.2 Diagnostic Utility and Performance of Earlyscreen: Participants were then presented with a description of the EarlyScreen prototype presented in this paper, including the predicted metrics, behavioral features used in

the predictive models, and classification performance for both neural activation and psychopathology prediction (see Appendix E for the full description). Based on this description, they were asked to rate their agreement with a series of statements relating to the diagnostic utility of EarlyScreen and its predicted outcomes and their willingness to incorporate such applications into their current practice. Figure 16 shows the participants' aggregate feedback on a scale of 1 ("Strongly disagree") to 5 ("Strongly agree"). Additionally, respondents also had the opportunity to comment on what they liked or disliked the most about EarlyScreen, what features they would like to see in a future version, and elaborate on any potential concerns they had. These comments are quoted here along with the participant ID.

Most of the respondents ($N = 42$ or 85.7%) agreed that *using home-based games such as EarlyScreen can help provide useful diagnostic information that can add to currently available methods*. Clinicians especially noted that such tools would "increase access to care for underserved communities" (P3) and "reduce the wait-list time" (P15) for accessing clinical services.

44 respondents (89.8%) said that such applications *could be useful for collecting ecologically valid data in home settings*. They also noted the advantages of EarlyScreen using a "child-friendly format" (P10) such that "it would be easy to engage children in using [EarlyScreen] and would provide complementary information to a traditional intake process" (P11). P24 also mentioned the utility of having access to "real-time information at home", while P38 noted the "passive ability to gather information".

Participants also felt that *neural activation levels* ($N = 34$ or 69.4%) and *psychopathological risk* ($N = 39$ or 79.6%) predicted by EarlyScreen could be useful for diagnosis in the future. P15 noted that EarlyScreen "can capture valuable data about brain activity that's not now available – and in a format that kids will easily engage with – data that's so relevant for early detection of developmental issues where early intervention matters so much in terms of outcome!".

40 participants (81.6%) also responded that *the preliminary accuracy of EarlyScreen's models is encouraging for future tests and subsequent deployment as an additional diagnostic tool*, with "higher percentage predictive value compared to behavior checklists" (P16).

23 respondents (46.9%) said they would *use and/or recommend an app such as EarlyScreen to clients/patients in addition to current intake practices*, while 21 others (42.9%) expressed a neutral opinion. 20 respondents (40.8%) disagreed that they would *be more likely to diagnose cases as [they] have always done than add a tool like EarlyScreen*, while 15 or 30.6% were neutral. The respondents elaborated on their reasons further, for example, P7 pointed out that "there would need to be explicit guidance on how to integrate info from the app with other assessments", P2 noted the presence of "institutional barriers and them not being flexible to introducing new techniques", and P31 was "concerned about startup costs and training".

Overall, clinicians demonstrated positive attitudes about EarlyScreen's utility and performance. Responses about using or recommending EarlyScreen also largely positive, and participants identified training resources that should be integrated into future versions for wider adoption.

8.2.3 Concerns for Deployment: Practitioners in our study were also asked about potential concerns related to the deployment of apps such as EarlyScreen. 27 participants (55.1%) expressed concerns about *data privacy*, wanting to "know how the data is stored" (P22) as well as information "on who develops, maintains, or monitors the app" (P7). Respondents also expressed concerns about *ethical considerations* ($N = 25$ or 51%) behind applications such as EarlyScreen. They noted a "concern about over reliance on something like this rather than a more full clinical assessment" (P29), which is in line with previous research on clinician attitudes towards other tools such as standardized assessments [74]. P27 pointed out that "facial recognition needs to be validated across physical characteristics ... it should be validated across groups", which we partially address in Section 8.1. Participants were also concerned about "the lack of consideration of child's environmental context in the assessment process" (P37) and "the need to standardize testing/assessment environment somewhat across homes (e.g., minimize potential

distractions from siblings, etc.)" (P33). Another concern was "about accessibility for families with limited access to high speed internet or smartphones" (P10). The *scientific validity of the methods used by EarlyScreen and similar apps* was also noted as a concern ($N = 25$ or 51%), with clinicians noting that "it still needs more validation" (P11) but also that they "want to understand how it was developed, read more about the validity and reliability" (P44). This can be explained by the lack of details in the overview of EarlyScreen that was provided (see Appendix E), with participants noting the need for published research in a "peer-reviewed journal explaining those processes, explaining methods, etc... Once that body of literature was established and I had a lot more information, my response would be on the upper end of the scale" (P27).

In summary, practitioners emphasized the need to ensure that data protection policies are in place and that standardization measures are taken while deploying EarlyScreen. In addition, follow-up work should examine the performance of the models in a broader population and further test the reliability and validity of EarlyScreen prior to its deployment in the wild.

8.3 Considerations for Mobile Deployment

In addition to ensuring ethical usage and consistent performance across demographic subgroups, EarlyScreen must be robust against various environmental and device-related factors for successful deployment in home settings. One such consideration is noisy video capture or the occlusion of children's faces during the task due to head movement or fidgeting, camera occlusion, or device positioning. To account for these factors, children in this study were not asked to maintain a fixed seating position or posture, and were free to move around in the seat, look around, talk to the experimenter, and behave as they would in an unsupervised setting at home.

Furthermore, we examined the amount of movement exhibited by our participants during the feedback segments of the frustration-inducing task. We found that the children moved their head a mean distance of 341.7 centimeters per second relative to the fixed camera during the feedback segments on average, implying that our system is robust to a fair degree of human movement. We also use head pose and gaze direction as features in our models, enabling us to leverage inter-individual variability in movement to predict neural activation and psychopathology. Our system is also trained on data with some degree of facial occlusion due to movement and camera angle – 35.6% of the frames captured during positive or negative feedback had missing faces (or facial landmarks could not be captured with high confidence).

In addition to allowing for noise in the video capture process, our experimental conditions also emulate at-home gameplay on a tablet by using a stationary touchscreen monitor for the kids to interact with. The cameras used for data collection (Axis Communications PTZ Network Cameras) capture video at a resolution of 1080p and frame rate of 60Hz, which is easily achieved by current smartphone and tablet cameras.

We also implemented a pilot version of the frustration-inducing task on a Windows Surface Pro 6 tablet as shown in Figure 17. The touchscreen tablet runs the Windows 10 Pro operating system with an Intel Core i5 processor and 8 GB of installed RAM, and has a 5 MP front-facing camera that can capture 1080p HD video. OBS Studio was used for background video capture from the front-facing camera throughout the duration of the task. We profiled the performance of our task implementation on this device and report detailed statistics in Table 5. Our analysis shows that EarlyScreen can be easily deployed on existing commercial devices for use in a child's home. A larger-scale pilot study is currently underway to validate the usability and screening accuracy of the tablet application.

9 DISCUSSION

We now discuss the implications of this work for both mental health practitioners and UbiComp researchers. We also discuss the fairness and ethical considerations of deploying EarlyScreen in the real world, describe its limitations, and delineate some future research directions.

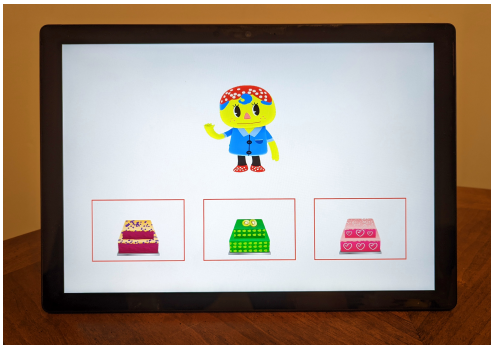


Fig. 17. Implementation of the frustration-inducing task on a Windows Surface Pro tablet.

Table 5. Profiling characteristics of the frustration-inducing task on a Windows Surface Pro tablet.

	Frustration Task GUI	Background Video Capture
CPU Utilization	4.66%	20.32%
Memory Usage	7.4 MB	159.1 MB
Power Consumption	2173 mW	755 mW

9.1 Implications for Clinical Psychology

The results of the present study have clear implications for the diagnosis of mental disorders in early childhood. Identifying mental disorder in children as young as preschoolers is very difficult as the symptoms of disorder closely resemble normative misbehavior [123] and many diagnostic instruments commonly used in real-world clinical settings have AUCs in the 0.7 range [21, 69]. Moreover, accessing these diagnostic services often places a significant burden on parents [24] and millions of children go undiagnosed and untreated each year [131]. To our knowledge, this study was the first to attempt to classify disorder status from standard streaming video. The fact that this initial effort achieved similar accuracy to instruments commonly used in the field, using automated methods that could be administered at home suggests the exciting possibility that ubiquitous computing methods could improve the accuracy of and reduce barriers to obtaining an early diagnosis. As noted by the mental health professionals surveyed, EarlyScreen provides the "ability to collect behavioral information in real world setting" (P26) in a way that "feels natural to the child and not like an evaluation" (P27) and "doesn't need connection to official medical services to use" (P44).

Moreover, EarlyScreen showed not only surprisingly good detection of disorder status, but detection of individual differences in PFC activation during frustration, a key neural mechanism that drives the development of mental illness [32, 36, 78]. Building on this finding may facilitate the development of diagnostic tools that allow clinicians to account for neural activation in their clinical decision making, providing "valuable data about brain activity that's not now available" (P15). Further, results suggest it is possible to infer coarse-grained PFC activation during emotion regulation using our proposed models with any mobile platform with a front facing camera, without requiring specialized neuroimaging hardware. Future research may therefore be able to study the early development neural underpinnings of early childhood mental health disorders at a much larger scale than is currently possible.

9.2 Implications for UbiComp Research

There is burgeoning interest among UbiComp researchers studying mental health to measure neural, physiological, and behavioral markers of mental disorders. Researchers have recently shown that resting state functional connectivity between the subgenual cingulate cortex and the ventromedial/orbitofrontal cortex is correlated with smartphone screen time [68] and that smartphone usage can predict functional connectivity [98] between the ventromedial prefrontal cortex and the amygdala – both of which have important implications for diagnosing depression and anxiety-related disorders. EarlyScreen further demonstrates how sensing tools can leverage the

association between neural and behavioral responses to support the diagnosis of psychopathology related to emotion dysregulation.

We also introduce a multi-trial frustration-inducing task with baseline, positive, and negative feedback periods that can be easily deployed as a gamified smartphone application. The task (or "game") is self-contained, which means that parents or caregivers can simply download the application and let children "play" it without additional setup or clinical intervention. The application can then utilize the device's front-facing camera to assess children's risk in real time and share the results with a caregiver, teacher, or clinician. A pilot implementation of such an application is described in Section 8.3. EarlyScreen can also be used to collect contextual information about children's behavior at home, allowing mental health practitioners to track children's progress or response to clinical interventions over time without requiring additional clinical visits. This would lead to more ecologically valid data for diagnosis compared to current methods of in-clinic behavior observation sessions.

While EarlyScreen utilizes vision-based techniques for monitoring neural activity during naturalistic instances of emotion regulation, there is also potential for using wearable devices for this purpose. There has been work in the UbiComp community on the detection of upper facial AUs using eyeglass-type wearables [107]. Movement, head pose, and eye gaze can also be detected using a variety of wearable devices with cameras and inertial sensors (e.g., [31, 66, 134]). These devices can potentially be used to continuously monitor AUs and other facial features and to detect neural activation levels in the wild. Further research is required to determine the accuracy of such systems trained with a subset of features and in more challenging contexts.

Our work also introduces a novel machine learning framework based on multi-scale instance fusion. This architecture can be adapted and used for both classification and regression problems in a number of domains beyond mental health applications. Drawing on core ideas from ensemble learning and multiple instance learning, we believe that our framework can be used to improve prediction performance in scenarios where the experimental design involves multiple trials, including but not limited to longitudinal data collected over multiple sessions or days. It can also be useful for prediction problems with audio, video, or image data where features extracted at multiple spatio-temporal resolutions can be combined in a similar manner. Such experimental paradigms are quite common in UbiComp research, and we believe that our framework will be a useful tool for researchers who encounter these scenarios in their work.

9.3 Limitations and Future Work

Our work is an exploratory proof of concept for predicting neural activation and clinical diagnostic status using facial expressions and movement-related features, and thus has limitations that will be addressed in future research. EarlyScreen depends on OpenFace 2.0 to extract AUs accurately, and extracted AUs have not been compared with manual FACS coding to verify their accuracy. As discussed previously, preschool-aged children also tend to look around, cover their faces with their hands, or otherwise move in a way that their faces are partially occluded from the camera's field of view at times. These could cause errors in AU recognition – however, OpenFace reports an average concordance coefficient of 0.73 using a baseline validation dataset [11].

Another limitation of our work is the relatively small sample size ($N = 76$) in training our models, however, our 5-fold cross-validation results and demographic analysis are encouraging for real-world deployment. To further assess the real-world generalizability of our system, we are also in the process of conducting at-home validation studies using the tablet-based implementation of our clinically-validated frustration-inducing task. Following this, we aim to engage diverse stakeholders including parents, caregivers, and child psychologists in a human-centered design process to create the final implementation of EarlyScreen. Our survey of clinical practitioners is a step in this direction, allowing us to discover the concerns they have about the future deployment of EarlyScreen.

10 CONCLUSION

In this work, we presented EarlyScreen, a system utilizing facial expressions and movement-related features from videos to characterize emotion regulation during frustration in preschool-aged children. We conducted an exploratory study with 94 participants where we recorded facial videos as well as neural activation using fNIRS while the children were engaged in a frustration-inducing task. We first attempted to classify low vs. normal activation levels in the PFC using features extracted from facial action units exhibited during positive and negative feedback. We trained and evaluated a novel machine learning framework, the Multi-scale Instance Fusion (MIF) framework, to classify activation levels. Our model succeeded in classifying PFC activation with an area under the ROC curve of 0.85. Next, we showed that behavioral features could also be used to predict psychopathology diagnosis using our MIF framework, achieving an area under the ROC curve of 0.80. The performance of EarlyScreen is on par with that of widely-used clinical assessment tools and consistent with individuals' scores on clinically-validated psychometric evaluation scales. Furthermore, we received positive feedback on the clinical utility of EarlyScreen from a survey of 60 child mental health professionals. We hope that our work is a step towards developing behavioral sensing solutions to better understand the neural underpinnings of psychopathology.

ACKNOWLEDGMENTS

This work was supported by the National Institute of Mental Health grant NIMH K23 MH111708 and the National Science Foundation grants 1839999, 1951928, and 1815347. This work was performed in part using high performance computing equipment obtained under a grant from the Collaborative R&D Fund managed by the Massachusetts Technology Collaborative.

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A FACIAL ACTION UNITS

Table 6 lists the facial action units (AUs) that were extracted from participants' videos using OpenFace. For each of these AUs, OpenFace provides frame-level presence/absence information. Additionally, it also detects the intensity of all AUs except AU 28. We group a subset of the AUs into positive and negative expressions based on prior literature, and use the presence of these expressions with and without eye constriction (AU 06) as features.

Table 6. List of FACS Action Units (AUs) extracted from videos. AUs were grouped into those signifying negative expressions and positive expressions (masking) based on prior work [58]. We also extracted additional uncategorized AUs which could potentially be useful in categorizing neural activation.

Category	Action Units (AUs)	Description of AUs
Negative Expressions	AU 4	Brow lowerer
	AU 7	Lid tightener
	AU 9	Nose wrinkler
	AU 10	Upper lip raiser
	AU 15	Lip corner depressor
	AU 23	Lip tightener
Positive Expressions (Masking)	AU 12	Lip corner puller
Eye Constriction	AU 6	Cheek raiser
Others	AU 1	Inner brow raiser
	AU 2	Outer brow raiser
	AU 5	Upper lid raiser
	AU 14	Dimpler
	AU 17	Chin raiser
	AU 20	Lip stretcher
	AU 25	Lips part
	AU 26	Jaw drop
	AU 28	Lip suck
	AU 45	Blink

B BAG REPRESENTATIONS FOR MULTIPLE INSTANCE LEARNING

- **Mean Mapping:** A trivial mapping from instance features to bag features is the arithmetic mean of each instance feature.

$$\mathbf{B}_{\mathbf{i}}^{\phi} = \left(\frac{1}{n_i} \sum_{x \in \mathbf{x}_{\mathbf{ij}}} x_1, \frac{1}{n_i} \sum_{x \in \mathbf{x}_{\mathbf{ij}}} x_2, ..., \frac{1}{n_i} \sum_{x \in \mathbf{x}_{\mathbf{ij}}} x_d \right)$$

- **Minimax Mapping:** The Minimax mapping proposed by Gartner et al. [55] represents a bag with the minimum and maximum of each feature over all instances.

$$\mathbf{B_i^\phi} = \big(\min_{x\in\mathbf{x_{ij}}} x_1, \min_{x\in\mathbf{x_{ij}}} x_2, ..., \min_{x\in\mathbf{x_{ij}}} x_d, \max_{x\in\mathbf{x_{ij}}} x_1, \max_{x\in\mathbf{x_{ij}}} x_2, ..., \max_{x\in\mathbf{x_{ij}}} x_d\big)$$

  Both Mean and Minimax mapping represent common statistical functions used to aggregate data from a series of observations.
- **Minimax Kernel Mapping:** Gartner et al. [55] also propose a polynomial minimax kernel such that

$$s(\mathbf{B_i}) = \big(\min_{x\in\mathbf{x_{ij}}} x_1, \min_{x\in\mathbf{x_{ij}}} x_2, ..., \min_{x\in\mathbf{x_{ij}}} x_d, \max_{x\in\mathbf{x_{ij}}} x_1, \max_{x\in\mathbf{x_{ij}}} x_2, ..., \max_{x\in\mathbf{x_{ij}}} x_d\big)$$

  and the bag representation takes the form of a polynomial positive definite Mercer kernel such that

$$k(\mathbf{B_i}, \mathbf{B_j}) = (\langle s(\mathbf{B_i}), s(\mathbf{B_j})\rangle + 1)^p$$

  where $\langle\cdot,\cdot\rangle$ denotes the inner product. This representation can be thought of as a generalization of support vector machines and other kernel methods.
- **MInD Mappping:** Represents each bag $\mathbf{B_i}$ as a vector of dissimilarities

$$\mathbf{B_i^\phi} = [d(\mathbf{B_i}, \mathbf{B_1}), d(\mathbf{B_i}, \mathbf{B_2}), ..., d(\mathbf{B_i}, \mathbf{B_M})]$$

  for all M bags in $\mathcal{T}$, where $\mathcal{T}$ is a subset of the training set, $|\mathcal{T}| = M$ and $M \leq N$ where N is the number of bags in the entire training set.
  For our implementation, we use $M \leq N$ and $d(\mathbf{B_i}, \mathbf{B_j})$ is the mean-min dissimilarity as proposed in the original implementation by Cheplygina et al. [30].

$$\mathbf{B_i^\phi} = [d(\mathbf{B_i}, \mathbf{B_1}), d(\mathbf{B_i}, \mathbf{B_2}), ..., d(\mathbf{B_i}, \mathbf{B_M})],$$
$$d(\mathbf{B_i}, \mathbf{B_j}) = d_{meanmin}(\mathbf{B_i}, \mathbf{B_j})$$

- **CCE Mapping:** The Constructive Clustering Ensemble algorithm proposed by Zhou et al. [140] clusters all instances in the training set into d clusters. Bags are then represented by a binary feature vector of length d, where the k^{th} feature is 1 if the k^{th} cluster contains an instance of the bag.

$$\mathbf{B_i^\phi} = [1(\exists \mathbf{x_{ij}} \in C_1), 1(\exists \mathbf{x_{ij}} \in C_2), ..., 1(\exists \mathbf{x_{ij}} \in C_d)]$$

- **MILES Mapping:** In this algorithm proposed by Chen et al. [29], each bag is represented in terms of a vector of similarities with each instance in the training set $\mathcal{T}$. If the number of instances in $\mathcal{T}$ is n, then

$$\mathbf{B_i^\phi} = [s(\mathbf{x^1}, \mathbf{B_i}), s(\mathbf{x^1}, \mathbf{B_i}), ..., s(\mathbf{x}^n, \mathbf{B_i})],$$
$$s(\mathbf{x^k}, \mathbf{B_i}) = \max_j \exp\left(-\frac{||\mathbf{x}_{ij} - \mathbf{x^k}||^2}{\sigma^2}\right)$$

- **Discriminative Bag Mapping:** The aMILGDM algorithm proposed by Wu et al. [133] is similar to MILES mapping, but each bag is represented as a vector of similarities with each instance in a Discriminative Instance Pool $\mathcal{P}^*$ instead of each instance in the training set $\mathcal{T}$. The DIP $\mathcal{P}^*$ is a subset of m training instances chosen such that it is maximally discriminative in the new feature space:

$$\mathcal{P}^* = \max_{\mathcal{P}\subseteq\mathcal{X}} \sum_{x_k^\phi \in \mathcal{P}} f(x_k^\phi, L) \; s.t. \; |\mathcal{P}| = m$$

  Here $\mathcal{X}$ is the set of all instances in the training set, x_k^ϕ are candidate instances in $\mathcal{P}$, and $f(x_k^\phi, L) = \phi_k^T L \phi_k$ where L is the Laplacian of the label embedding matrix and ϕ_k is given by

$$\phi_k = [s(\mathbf{B_k}, \mathbf{x^1}), s(\mathbf{B_k}, \mathbf{x^2}), ..., s(\mathbf{B_k}, \mathbf{x^n})]$$

for all n instances in the training set. Once $\mathscr{P}^*$ is computed as above, the bag features are computed similar to the MILES representation using instances in $\mathscr{P}^*$.

C MODEL IMPLEMENTATION AND HYPERPARAMETER CHOICES

Table 7. Machine learning algorithms evaluated and the set of hyperparameters considered for each algorithm.

Algorithm	Hyperparameters	Hyperparameter Choices
Dimensionality Reduction		
Principal Component Analysis	n_components	2, 5, all
	whitening	True, False
Supervised Learning Algorithms		
Logistic Regression	C	0.001, 0.01, 0.1, 1, 10
	Penalty	l1, l2
Random Forest Classifier	No. of estimators	5, 10, 20, 50, 100, 200, 500
	Maximum depth	2, 3, 5, 10
	Minimum samples to split	2, 3, 5, 10
Gradient Boosting Classifier	No. of estimators	20, 50, 100, 200, 500, 1000
	Learning rate	0.01, 0.1, 1, 10
	Minimum samples to split	2, 3, 5, 10
AdaBoost Classifier	No. of estimators	20, 50, 100, 200, 500, 1000
	learning rate	0.01, 0.1, 1, 10
Gaussian Naive Bayes	no hyperparameters	-
Support Vector Classifier with RBF kernel	C	0.001, 0.01, 0.1, 1, 10
	gamma	0.0001, 0.001, 0.01, 0.1, 1
k-Nearest Neighbors	k	1, 2, 5, 10
	weights	uniform, distance
MIL Bag Representation Algorithms		
Mean Mapping	no hyperparameters	-
Minimax Mapping	no hyperparameters	-
Polynomial Minimax Kernel	p	1, 2, 3, 4, 5, 6
MIND Mapping	no hyperparameters	-
CCE Mapping	d	2, 3, 5, 10, 20
MILES Mapping	σ^2	10, 20, 50, 1e2, 5e2, 1e3, 5e3, 1e4, 5e4, 1e5, 5e5, 1e6
Discriminative Bag Mapping	σ^2	10, 20, 50, 1e2, 5e2, 1e3, 5e3, 1e4, 5e4, 1e5, 5e5, 1e6

Table 7 shows the classifier choices for the supervised learning module and the MIL mappings for the bag representation module considered in our work. We also list the hyperparameter choices associated with each algorithm that were evaluated as part of our randomized hyperparameter search procedure (see Section 5).

The feature sets used for training are listed in Section 4.3. The supervised learning module contained a dimensionality reduction step that filtered features with zero variance and applied principal component analysis.

The resulting principal components are scaled before being passed to the classifier. Data imbalance is handled by using a class-balanced weighting for the loss function for all classifiers. This was empirically found to provide better performance than both random and synthetic under/oversampling. Similar pipelines are used for both neural activation and psychopathology classification.

D DEMOGRAPHIC INFORMATION

The demographic information collected from participants in this study included data on gender, age, race (choose as many as applicable from American Indian or Alaska Native, Asian, Black or African American, Native Hawaiian or Other Pacific Islander, White, N/A), and ethnicity (choose one of Hispanic or Latino, Not Hispanic or Latino). Participants were grouped by demographic subgroups as listed in Table 8. Race and ethnicity were combined into a single indicator of racial group (White, Black, Multiracial, Other, N/A) for easier quantitative analysis of model performance across subgroups.

Table 8 also shows the number and percentage of participants within each subgroup that exhibited low neural activation (less than 1SD below mean) and clinical psychopathological symptoms (scoring higher than clinical threshold on any scale).

Table 8. Demographic composition of our study population and percentage of participants exhibiting low neural activation or clinical symptoms in each subgroup.

Demographic Group	Number of Participants	Number of participants with Low Neural Activation	Number of Clinical Participants
Gender			
Male	37	4 (10.8%)	13 (35.1%)
Female	37	8 (21.6%)	12 (32.4%)
Age Group			
3-4 years	19	3 (15.8%)	10 (52.6%)
4-5 years	32	6 (18.8%)	9 (28.1%)
5-6 years	23	3 (13%)	6 (26.1%)
Race			
White	48	9 (18.8%)	18 (37.5%)
Black	7	1 (14.3%)	1 (14.3%)
Multiracial	7	1 (14.3%)	3 (42.9%)
Other	11	1 (9.1%)	3 (27.3%)
N/A	3	-	-

E SURVEY DESCRIPTION

Participants filling the survey were asked for feedback based on the following description of EarlyScreen:

> We will now describe **EarlyScreen**, a prototype digital mental health screening tool that has been designed to help parents, caregivers, and clinicians identify specific disorders common in early childhood. EarlyScreen is an additional at-home tool meant to complement existing clinical practices.

One possible use for EarlyScreen is to make the diagnostic intake procedure more efficient and convenient for clinicians and families, particularly low-resource, low-income families. For example, EarlyScreen could be used with a family on the waitlist who urgently needs to pivot to treatment, a low-income family who has difficulty attending multiple in-person intake appointments, or a clinician looking for diagnostic information from a modality other than questionnaires or observation. It could also be used as an additional tool to track changes over the course of therapy.

- *EarlyScreen is a smartphone- or tablet-based "game" that can be played by preschool-aged children that is modelled after existing iPad games.*
- *The game will induce frustration in children using a clinically-validated paradigm and record facial videos during the process using the tablet's front camera. (In the current iteration, the game involves providing negative feedback on children's choices – see link for more information).*
- *Facial expressions and head and eye movements are extracted from the captured video and used by machine learning models to predict:*
  - *neural activation within the prefrontal cortex, a region of the brain involved in emotion regulation.*
  - *the child's score on a series of clinically-validated questionnaires to screen for externalizing disorders and ADHD.*

In lab-based tests with 76 participants, a prototype of EarlyScreen could correctly identify 75% of the children exhibiting abnormally low neural activation in the prefrontal cortex during frustration and 77% of children exhibiting normal levels of neural activation. (For context, the Child Behavior Checklist – a well-validated screening tool – correctly identifies 66% of children with exhibiting problematic behavior).

EarlyScreen could also correctly identify 72% of children who scored above clinical thresholds on the CBCL Externalizing disorders, MAP-DB temper loss, and ADHD Inattention and Hyperactivity scales and 76% of children who were below the clinical thresholds.