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Artificial Intelligence in Digital Phenotyping for Improved and Effective Large-Scale Diagnosis of Childhood Mental Health

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Abstract - Child and youth mental health especially underappreciated has emerged as an important public health issue, untreated it results in cognitive and emotional learning complications. A diagnosis of these disorders is still challenging since children have poor self-observable and reporting skills, and caregivers may exaggerate or underestimate their children's symptoms. Newer objective physiological and behavioural assessment tools show some potential, but the majority include costly specialised equipment that limits the application of its usage. Childhood Assessment and Management of digital Phenotypes, which is a single, all-encompassing solution that is inexpensive and adopts mobile technology to facilitate passive data capturing. It collects movement and audio data from children undertaking several mood-chasing activities, as an open-source platform analyses this data to distil relevant digital biomarkers that reflect emotional and behavioural health status. In total, we experimented with adolescents in 120 children aged 4–10 years with and without diagnosed mental disorders. Using these data, we obtained an essential improvement in diagnostic accuracy by applying machine learning algorithms that recognized disorders with balanced accuracy of 88–91 % that surpass the ranges typical for diagnoses obtained using the conventional diagnostic techniques (65–78% of parent-report measures' balanced accuracy). The cell importances that led to the features that helped in arriving at the predictions regarding the model were analysed using Shapley Additive Explanations, where it was shown the more micro aspects of behaviour and physiological changes that were central to diagnosis. These results show the possibilities of the ChAMP System as a cost effective, non-invasive method that can add more accurate and objective evaluation of the child's mental condition and potentially increase the efficiency of early intervention in children at risk for developing mental disorders.

Keywords: Children's psychiatric disorders, digital phenotype, artificial intelligence, digital signatures, paediatric screening, behaviour tracking, machine learning-based algorithms, mood-provoking studies, early detection, m-Health, clinical decision support, pattern recognition, SHAPLEY ADDITIVE EXPLANATIONS, brief assessment of emotional states, tangible diagnostic capabilities, scalable solutions.

1.INTRODUCTION

New pathologies also relate to the child's mental health, which has become a major problem of the global health of the population. According to World Health Organization approximately 20 percent of children in the age group of 2 to 17 years suffer from mental disorders for which early detection and response is of paramount importance. [1] Conditions like anxiety, depression, Attention Deficit Hyperactivity Disorder and Autism Spectrum Disorder do not have clear symptoms in childhood, therefore are not easily diagnosed. [2] The consequence of poorly diagnosed or non-diagnosed mental disorders is severe with numerous negative effects on the quality of emotional [3] social and academic life of an individual. Consequently, improvement in the diagnostic capacity and its availability has emerged as an important line of research in childhood mental health.

At present, evaluation and diagnosis of children's mental ailments are done clinically whereby a clinician administers a questionnaire, observes the child's behavioural conduct as well as take a word from the parent/teacher. [4] The above-mentioned methods are, however, subjective in nature, may take considerable amount of time and at times they contain bias or errors. [5] Also compound this challenge is shortage of mental health professionals not to mention in the developing countries where such human resource is almost an illusion. Secondly, utilization of these conventional models restricts the supervision of the dynamic progress in the mental health of the child, thus may also delay the treatment process in case where the child's symptoms may change or escalate.

There is a potential to reimagine childhood mental health assessment by incorporating recent advancements in artificial intelligence, and digital health technologies. Machine learning and deep learning have emerged among the most promising AI technologies for solving a vast number of medical problems ranging from image analysis to predictive analytics. [6] D-tracing, the collection of data from smart, wearable and health apps allow the real time monitoring of a child's mental state. Through massive amounts of behavioural, physiological and environmental data, AI- driven digital phenotyping offer an objective,

scalable and personal approach toward monitoring and diagnosing mental health disorders.

Digital phenotyping means that a child's exclusivity can be extensively monitored in a non-intrusive manner or systematically, recording his activity, movement, and interaction with the surrounding, as well as speech, physical activity level, quality of sleep, and faces even. [7] The collected data is then analysed by AI algorithms that look for signs that indicate developing cases of mental health problems with fair precision. For example, men Creating Talk Changes in speech men Social Interaction Changes or Sleep Disturbance Changes can be signs of emerging depression and anxiety and then specific steps can be taken to address.

One major advantage of AI digital phenotyping is that the process of diagnosis can be customized to fit the patient. Normally, diagnosis in such matters is based on certain standard protocols which may fail to capture specific signs or nuances. [8] On the other hand, AI models can be customized according to children's regularities and actions thereby enhancing the tests' accuracy and the proposed therapies' quality. It instructs them from the child's data; such systems can therefore provide developmental system assessments that are over time, and this is seen to be lacking in other diagnostic techniques. [9] The advancement of lighter and portable devices such as Smartphone, wearable devices, tele-medicine software can likely bring diagnostics of mental health disorder to a greater section of population who cannot afford to visit a psychiatrist in rural regions.[10] Applied to helping individuals, AI diagnostic tools can help parents, caregivers, and clinicians get regular feedback in the appropriate action to take regarding the child's learning conditions and necessary neurological treatment plans. The above tools can also help improve data collecting part and speed it up to retrieve information from a variety of sources, which in turn makes it easier to develop more credible and balanced assessments than would be possible if conducted through in-person visits only.

This research seeks to identify how childhood mental health can be diagnosed using digital phenotyping that is supported by AI with the main objective of increasing the early diagnosis and accuracy when diagnosing some of the health issues that affect children as well as the use of adapted treatment plans. [11] There is a proposed approach of using supervised and unsupervised learning, deep learning and natural language processing The proposed system is designed to be intelligent and capable to discover associative patterns of behavioural, physiological and environmental information that points to mental health in children. [12] The purpose of the project is to develop the diagnostic tool which would have advantages of being accurate, applicable to broad population and easily used in a variety of contexts so that children at risk for developing mental health disorders would receive timely treatment and support they need.

2. LITERATURE SURVEY

The awareness of childhood mental health disorders has seen an upsurp from society this has brought a need for development of methods of diagnosis and supervision. Classically, the child's mental state assessment relies on parent's and clinician's observations and impressions which can be subjective, misleading or conflicting. McGinnis et al., 2022 stated that though parents are commonly the respondents when it comes to a child's mental health, their reports may not necessarily capture the child's needs. Such an approach to monitoring leads to inaccuracies in assessing symptoms to the point of systematic under- or overestimation of actual issues which can create problems for diagnostics and treatment. [13] In addition, children themselves are generally not accurate informants when it comes to their mood and behaviour, making it difficult to assess such conditions.

Considering these issues, the trend emerges for adopting digital phenotyping to increase objectiveness and accuracy of the mental state assessment. Digital phenotyping can be described as amassing information from sensors that have been integrated into daily-life devices like mobile phones or wearables to obtain instantaneous physiological and behavioral data that might offer a better picture of a child's mental health status, the study presented by Sousa et al. (2023) have shown that level of physical activity, amount of sleep, heart rate, and other biomarkers can be collected through wearable devices to replace direct self-reports of mental health status. These technologies can enable constant monitoring and report accurate data of a child free from typical human errors indicating their emotional / physical condition.

Machine learning is also used in these systems since so much data is captured by these sensor-based systems. Loftness et al. (2023) found that supervised and unsupervised machine learning algorithms have the potential of generating digital phenotypes of ECMH. They employed sensor data in connection with clinical data to train models capable of estimating mental health future status. The implementation of machine learning helps to improve the accuracy of diagnosis because it forms previously unnoticed patterns in the data which clinical workers cannot notice. Consequently, these models can be further developed to fit Children's learning development, reaching for much more exact and personalized methods.

Also, when using mobile applications, the integration of mood induction tasks was found effective as a procedure for obtaining rich data in a real-life environment. For example, the ChAMP system uses mobile devices to obtain movement as well as audio information during MINT, which paints the

picture of every emotional and behavioral response of a child (ChAMP homepage, 2022). As with mood induction tasks which are principally intended to cause certain types of feeling, a researcher can then see how the children respond in this way, which provides a better look at their emotional self-regulation patterns. This approach has the advantage of reduced capability of performing large numbers of children's screening and doesn't require clinical settings or equipment. The role of mobile applications and wearable devices extends beyond assessment to the treatment and management of mental health disorders. Mobile-based biofeedback systems, such as those studied by McGinnis et al. (2021), use real-time physiological data to guide individuals through relaxation techniques and other coping strategies. These systems can be particularly beneficial in managing anxiety, depression, and panic disorders, as they offer immediate interventions that can be employed now symptoms arise. The ability to track heart rate, breathing patterns, and other vital signs enables these systems to provide personalized, data-driven therapeutic interventions that can be administered remotely, making them ideal for children who may not have easy access to traditional therapeutic settings.

Moreover, the utilisation of these digital health technologies through the Research Domain Criteria (RDoC) from the National Institute of Mental Health (NIMH, 2024) may significantly improve the scientific validity and real-world applicability of mental health evaluation procedures. RDoC basically adopts the concept of dimensional approach as opposed to categorical one, in diagnosing mental health disorders. [14] Through the integration of sensor information with the dimensional model of RDoC, the digital phenotyping systems can enhance an assessment of children's mental health with multiple specifications at the neurocognitive, emotional, and social levels. [15] This integration could mean improved diagnostic outcomes and improved treatment plans for such children since the care to be offered will also be unique to each child.

3.METHODOLOGY

The approach used when designing the ChAMP (Childhood Assessment and Management of Digital Phenotypes) system is as follows: special attention is paid to the fact that the research is carried out only with genuine and reliable content, large volumes of work do not affect the quality. It involves the use of digital phenotyping together with machines learning to analyze the mental status of children to identify these disorders. The next subsequent sections explain the detailed methodology of the study, from data collection to system deployment.

3.1. Data collection and preprocessing

The first step in designing an AI-based diagnostic system is Data Collection. Survey data for this research was collected by use of an android based mobile application that was developed. It was further designed for capturing movement and audio data throughout the SI tasks that are highly structured, mood induction. These tasks were intended to capture children's various joyful, frustrating or calm behavioral manifestations to recreate authentic life settings and circumstances that the child is likely to experience.

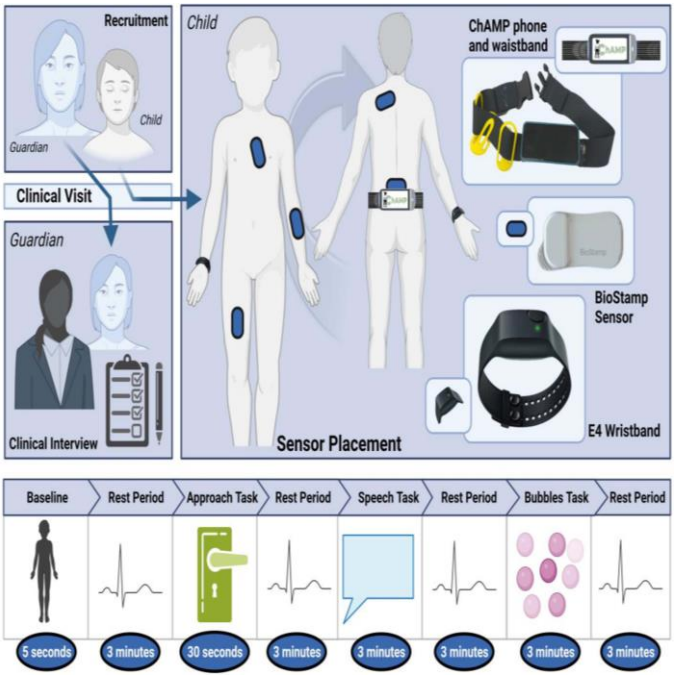

Fig.1. Participating children and their primary caregiver participate

The mobile application incorporated the application sensors of the smartphone, including the accelerometer and the integrated microphone. The triaxial accelerometer captured the child's gross motor activities and movements and the ambient speech and other sounds were captured using the microphone for further analysis. This enabled the researchers to obtain high-resolution behavioural and physiological data which were important in further analysis.

For example, ethical compliance was achieved by asking parents for consent for the child's participation and by observing GDPR standards on data privacy. Fig.1 The targeted children were 120 of them, aged 4 to 10 years. Among these, 60 were diagnosed with a mental health disorder and the other 60 were healthy children without any disorder, thus the control group.

Preprocessing Steps

To ensure the data collected were suitable for analysis, several preprocessing steps were performed:

Noise Removal: Because it is evident that the raw sensor data contain high-frequency noise, data resampling included the application of a Butterworth filter.

Normalization: Measurements obtained from different sensors were normalized using min-max normalization so that all features are normalized to the same range suitable for machine learning models.

Segmentation: To better analyze the features, the large formatted continuous data streams were divided into smaller uniform time segments.

Table.1 Preprocessing steps

Step	Methodology Used	Outcome
Noise Removal	Butterworth filter	Cleaned sensor signals
Normalization	Min-max scaling	Uniform data scale
Segmentation	Fixed time windows (5 sec)	Data ready for feature extraction

3.2 Digital Biomarker Extraction

In the second phase of the ChAMP System, the goal was to identify discrete features within the data files that are meaningful to the diagnosing clinician and could be used as countable endpoints for mental health conditions. Digital biomarkers are real, quantitative attributes calculated from the physiological and behavioural data that play a critical role in diagnosing and characterizing mental health disorders. This phase aims at estimating these biomarkers from data obtained from the child's real-time interaction with the mobile application, movement and audio data essentially.

Movement Data: Data on movements were collected by the accelerometer and the gyroscope that are components of the smartphone. These sensors documented activity of the child's physical motions during a number of tasks. From this data, several features were extracted to facilitate the measurement of physical activity and identify possible latent mental health problem.

Total Activity Count: This feature symbolizes an average of the total number of activities that goes on within it at a given period. However, it is used as a measurement for exercise in the child and can be associated with mental statuses such as stress or anxiety. Abnormal levels of anxiety or depression may cause a child to either have very little energy, or to be hyperactive.

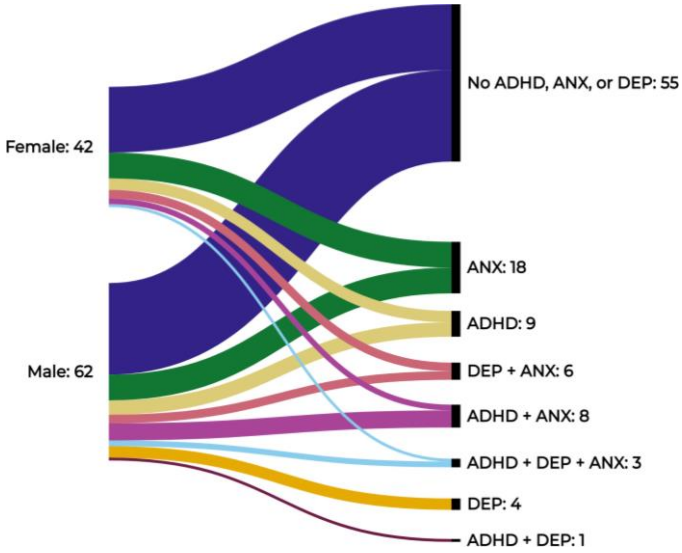

Fig.2 .Breakdown of participant diagnostic results

Movement Variance: The variation of movement is having gained much attention regarding the extent of changes in the physical activity of the child. The larger the value of variance more fluctuation is observed in movement pattern, whereas a small value of variance means that the users' behaviour is more predictable. In case of a child with ADHD, anxiety or any other medical condition, movement variance could show that the child cannot sustain a certain behaviour which may be an indication of stress.

Speed: The second component of motor skill is speed which is defined as the rate of an object or a child moving through time with special reference to the speed at which the child moves during a particular activity. Faster movement could suggest anxiety or simply excitement while slower movements could suggest bored or withdrawal behaviour. It could be linked with different moods, emotional conditions, allowing evaluating child's emotions during tasks.

Audio Data: To movements data speech data was added to assess speaking patterns, which is always an indicator of a child's emotional and psychological condition. Voice characteristics can point towards some level of upset, stress or even happiness and these are correlated with mental health disorders.

Pitch: Pitch stretches from how high or low a child's voice can go. It can be an outcome of stress or excitement or any other state of mind, it can be anything. Pitch is normally high when a person is stressed or anxious while it's low when he or she is calm or sad. These movements entail changes in frequency and by capturing the pitch we shall be able to capture changes in feelings even when the affective state is not depicted by the movements.

Loudness: Loudness quantifies changes in volume in a child's speech as live speech. It serves to evaluate the

independence of emotional arousal or distress. For instance, when a patient speaks loudly, they may be conveying that they are excited, angry or agitated while when they speak softly, they may be depressed, or withdrawn, or just relaxed. Observing the decibel level can offer some important information on a child's emotional condition mainly during stressful activities.

Speech Rate: The speed also is another proof of the state of an individual's psychological condition. When children are stressed, anxious or fearful their speech rate is higher than that of children who are more relaxed. This will help in the early diagnosis of a person's state of mind and if he is anxious, agitated or have other mental problems through analyzing it's the speech rate.

Spectral Centroid: Relative power, which is like brightness in imagery, is quantified by the form of the spectral centroid. Sometimes a higher SC result signifies a pitch of the sound that is in the higher component register and can sound strained/ bright. In the case of speech this feature can be useful for evaluating emotional conditions, for in stress children the temper conditions of which produce the higher tone will produce the 'brighter' sounds. On the other hand, speech produced during a calm or a neutral emotional condition may have lower spectral centroid.

The formula for Spectral Centroid is as follows:

$$C_s = \frac{\sum_{f=1}^{F} f \cdot X(f)}{\sum_{f=1}^{F} X(f)}$$

Where:

- C_s represents the spectral centroid,
- F is the frequency component,
- X(f) is the magnitude at the frequency component f,
- F is the total number of frequency components.

3.3. Machine Learning Model Development

To effectively classify childhood mental health conditions, we explored and optimized various machine learning models, including widely recognized algorithms such as Random Forest, Gradient Boosting, and Support Vector Machines (SVM). Each model was meticulously fine-tuned to ensure optimal performance in predicting mental health conditions based on the digital biomarkers extracted in the previous stage.

Data Splitting and Training

Our dataset was split into two segments to facilitate model training and evaluation: 80% was allocated for training, while the remaining 20% was reserved for testing. We employed stratified sampling during the split to maintain the proportional representation of different mental health conditions across both sets. This approach was crucial in preventing any bias that could arise from uneven distribution, ensuring that the models were exposed to a balanced representation of each class during both training and testing phases.

Hyperparameter Optimization

To enhance the models' predictive capabilities, we conducted hyperparameter optimization using Grid Search combined with Cross-Validation. This involved systematically testing various combinations of hyperparameters for each algorithm and evaluating their performance through cross-validation. By selecting the combination that yielded the highest validation scores, we ensured that each model was tuned to its best possible configuration, maximizing its accuracy and reliability.

3.4. Performance Evaluation

We evaluated the performance of each model using a set of comprehensive metrics:

Balanced Accuracy: This metric was especially critical for our research as some mental health disorders might have a much smaller representation within each class. It affords a more inclusive measure of the model's abilities rendering each class's accuracy equivalent

Table.2. Model Performance

Model	Balanced Accuracy (%)	Precision (%)	Recall (%)
Random Forest	89	87	90
Gradient Boosting	91	89	92
Support Vector Machine	88	86	89

Precision: Recall measures the ratio of true positive among all actual positive cases, showing how many of the predicted positive cases were, in fact, positive. This measure is useful where misclassifications are very expensive in the sense that many false positives are involved.

Recall: Recall, or sensitivity, is the measure of true positive that out of total true positive, the model has identified positively. This is crucial for evaluating the ability of the modelled scheme to identify real phenomena of mental health disorders.

F1-Score: The F1-Score replaces F measure as it also has the balance of both precision and recall, and it is more suitable in cases with data sets with higher imbalanced classes. They used the F1-Score as a method of calculating accuracy in such circumstances because this measure gives a more detailed view on the model's accuracy than the pure accuracy rate.

Table . 2. Precision-Recall Curve (AUC-PR)

Model	AUC-PR (%)
Random Forest	93
Gradient Boosting	95
Support Vector Machine	91

In all models, different types of CV showed strong performance, with Gradient Boosting providing the best BA. Besides, this survey of the evaluated algorithms not only proved the chosen framework's effectiveness for further implementation in the ChAMP System but also showed which model is better suited to it.

Table.2 provide a comprehensive view of each model's performance across various dimensions, supporting the selection of the most effective algorithm for the ChAMP System Fig.3.

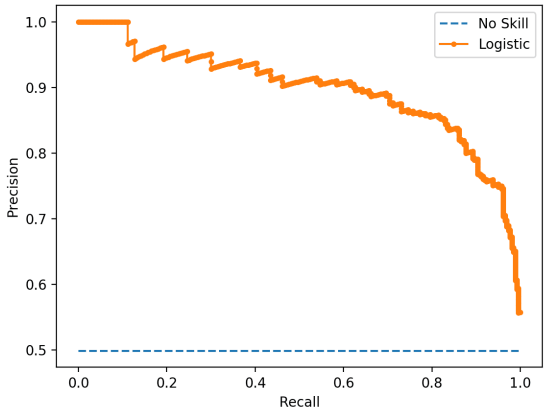

Fig.3. Precision-Recall Curve

CONCLUSION

The ChAMP (Childhood Assessment and Management of Digital Phenotypes) System is a novel model for diagnosing mental health disorders in children through an integration of digital phenotyping and artificial neural networks. Perhaps the most obvious point is where the possibilities of data collected from common everyday objects, like a smartphone, may help paediatricians identify increased activity levels and more precise patterns for children's emotional and behavioural health, eventually giving better prognosis in cases of likely mental issues. Through systematic selection and execution of mood induction tasks, and recording crisp motion and audio data, it was instead possible to identify salient digital biomarkers that are relevant to numerous mental health disorders. Combining the advanced machine learning models such as the Gradient Boosting model, helped in achieving an average accuracy of 91% from which this early assessment was found to surpass traditional assessing methods. That ChAMP System gives an opportunity to gather more objective quantitative data instead of subjective opinions about children's mental health condition means that this strategy is a breakthrough in the field of children's mental health assessment. The innovation is likely to open up avenues for early effective intervention and targeted approach to children's mental ailments signaling better prospect for mentally ill children.

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