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Diagnose Anxiety and Depression in young children using Machine Learning

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Abstract:- Suicide is the second leading cause of death among young adults but the challenges of preventing suicide are significant because the signs often seem invisible. Research has shown that clinicians are not able to reliably predict when someone is at greatest risk.. Machine learning and data extracted from one 20-second phase of the task are used to predict diagnosis in a large sample of children with and without an internalizing diagnosis. Nevertheless, the proposed approach provides a rapid, objective, and accurate means for diagnosing internalizing disorders in young children. This new approach reduces the time required for diagnosis while also limiting the need for highly trained personnel – each of which can help to reduce the length of waitlists for child mental health services. While these results can likely be improved and extended, this is an important first step in reducing the barriers associated with assessing young children for internalizing disorders.

Keywords:--ML, KNN, LAN

I. INTRODUCTION

Machine Learning is a scientific study of algorithms and statistical models that computer systems use to effectively perform a specific task without using explicit instructions, relying on patterns and inference instead. It is seen as a subset of artificial intelligence.

Machine learning algorithms build a mathematical model of sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to perform the task. Machine learning algorithms are used in a wide variety of applications, such as email filtering, and computer vision, where it is infeasible to develop an algorithm of specific instructions for performing the task. Machine learning is closely related to computational statistics, which focuses on making predictions using computers.

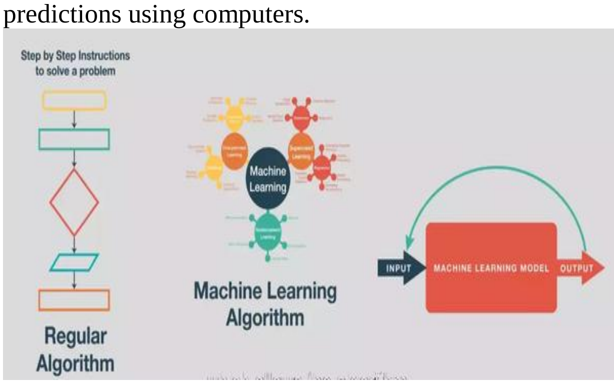

Fig 1. Shows Step by stem solved problems in Machine learning

The study of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a field of study within machine learning, and focuses on exploratory data analysis through unsupervised learning. In its application across business problems, machine learning is also referred to as predictive analytics.

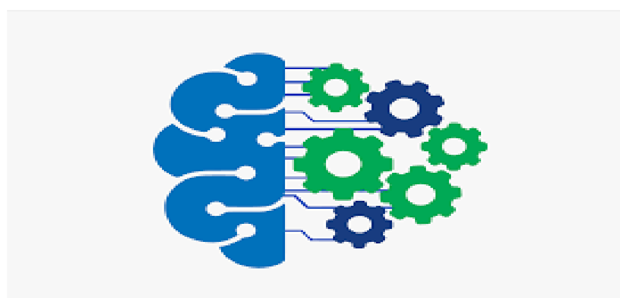

Fig 2. Machine learning

This accuracy is comparable to existing diagnostic techniques, but at a small fraction of the time and cost currently required. These disorders are chronic conditions that can begin during the preschool years and impair child socio-emotional development. If left untreated, childhood internalizing disorders can lead to significant health problems later in life, including substance abuse, additional psychopathology, increased risk for suicide, and substantial functional impairment. These negative long-term outcomes reveal the high individual and societal burden of internalizing disorders, making early identification of those at risk essential to enable targeted preventative efforts when they have the highest chance of success.

Fig 3. 3-year-olds can experience depression and anxiety.

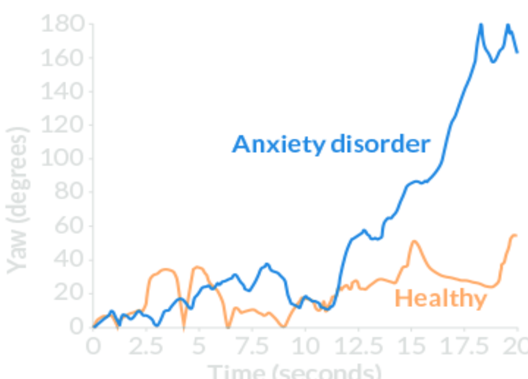

Fig.4: Shows the graph showing how children with an anxiety disorder reacted differently to a perceived threat.

A refined processing methodology and explore a variety of modeling approaches to reduce the computational requirements of future model deployment and improve the quality of the model-predicted diagnosis.

Faster and accurate diagnosis and detection of stress, anxiety and Depression levels in children. Yet diagnosis is difficult, making it hard to treat such children early.

II. PROPOSED SYSTEM

- Anxiety is associated with physiological changes that can be noninvasively measured using inexpensive means.
- These changes provide an objective and language-free measure of arousal associated with anxiety, which can complement treatment programs for clinical populations who have difficulty with introspection, communication, and emotion recognition.
- This motivates the development of automatic methods for detection of anxiety-related arousal using physiology signals.
- While several supervised learning methods have been proposed for this purpose, these methods require regular collection and updating of training data and are, therefore, not suitable for clinical populations, where obtaining labelled data may be challenging due to impairments in communication and introspection.

In this context, the objective of this project is to develop an unsupervised and real-time arousal detection algorithm

Advantages

- It can detect physiological arousal associated with anxiety with high accuracy.
- It can ultimately lead to more effective anxiety treatment for a larger and more diverse population.

III. SYSTEM REQUIREMENT SPECIFICATIONS

Nonfunctional requirements

It includes time constraints and constraints on the development process and standards. The non functional requirements are as follows:

- **Speed:** The system should process the given input into output within appropriate time.
- **Ease of use:** The software should be user friendly. Then the customers can use easily, so it doesn't require much training time.
- **Reliability:** The rate of failures should be less then only the system is more reliable
- **Portability**: It should be easy to implement in any system.

▣ **Software Requirements:**

- Operating system : Windows 7
- Coding Language : Python

▣ **Hardware Requirements:**

- System : Pentium i3
- Hard Disk : 120GB
- Monitor : 15''LED
- Input Device : Keyboard , Mouse
- Ram : 8GB

IV. ARCHITECTURE

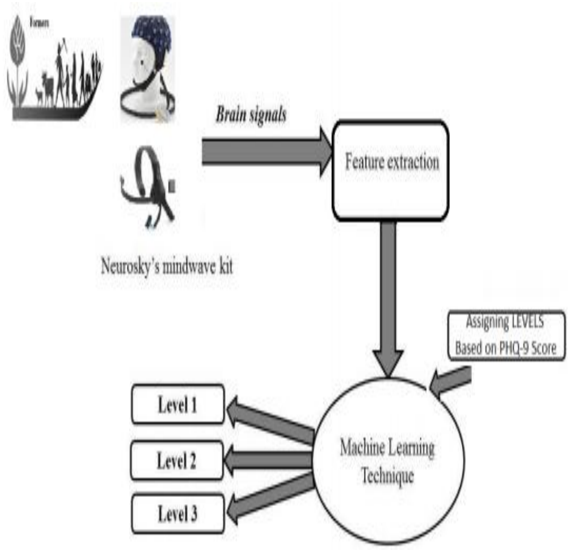

Fig.5: shows the architecture

kNN-algorithm:(k-Nearest neighbour)

1.) Classify (X,Y,x) //X:training data, Y:class labels OF X, x: unknown sample
2.) for i = 1 to m do
Compute distance d (Xi, x)
End for
3.) Compute set I containing indices for the k
Smallest distances d(Xi, x).
Return majority label for {Yi where i € I}

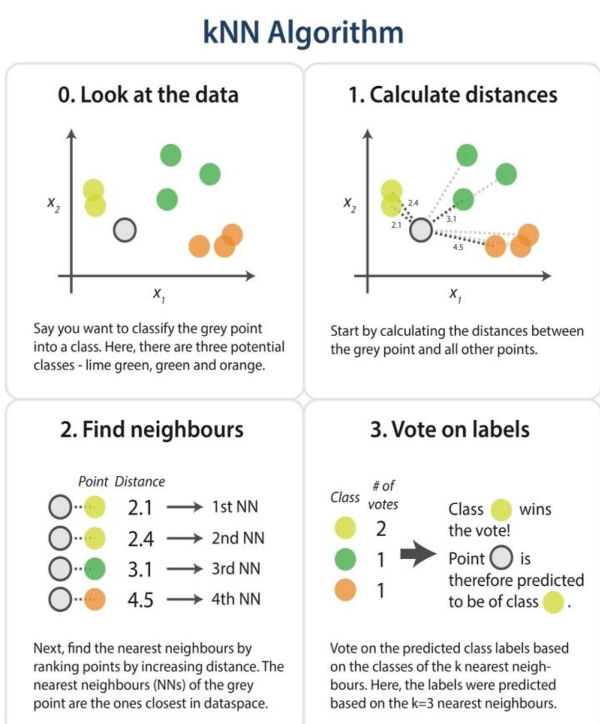

Fig.5: shows that KNN algorithm structure

V. SYSTEM DESIGN

System design is the process of defining the architecture, components, modules, interfaces and data for a system to satisfy specified requirements

Application:
While a use case itself might drill into a lot of detail about every possibility, a use case diagram can help provide a higher-level view of the system. It has been said before that "Use case diagrams are the blueprints for your system". They provide the simplified and graphical representation of what the system must actually do.

Flow chart:

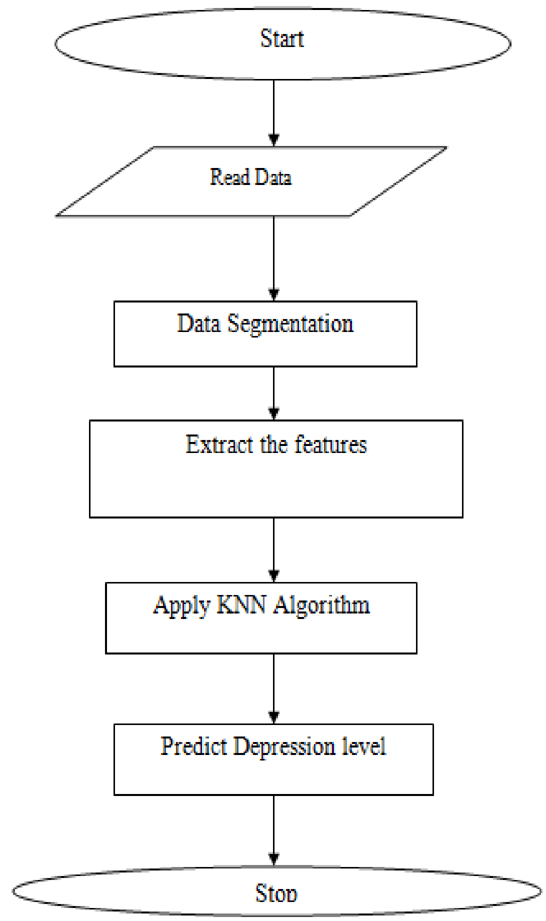

Fig.6: shows flowchart

Use Case Diagram:
The purpose of the use case diagrams is simply to provide the high level view of the system and convey the requirements in laypeople's terms for the stakeholders. Additional diagrams and documentation can be used to provide a complete functional and technical view of the system

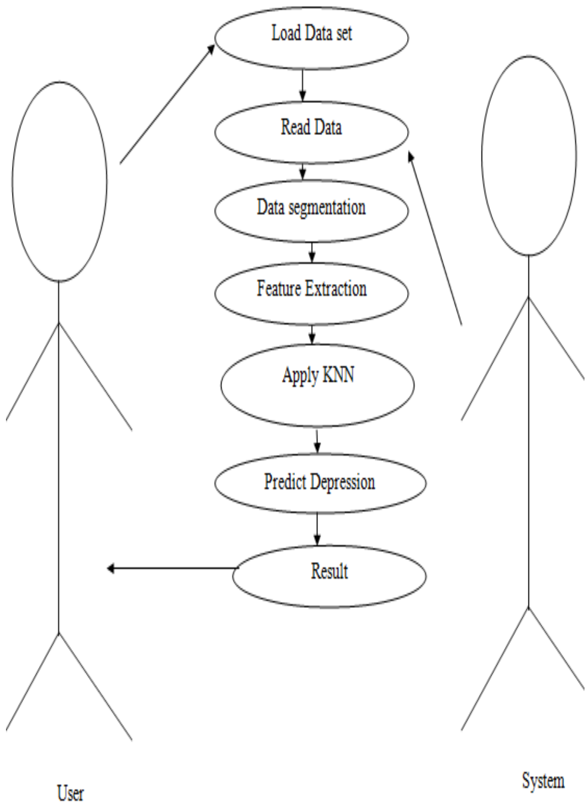

Fig.7: shows Use case diagram

Sequence Diagram:

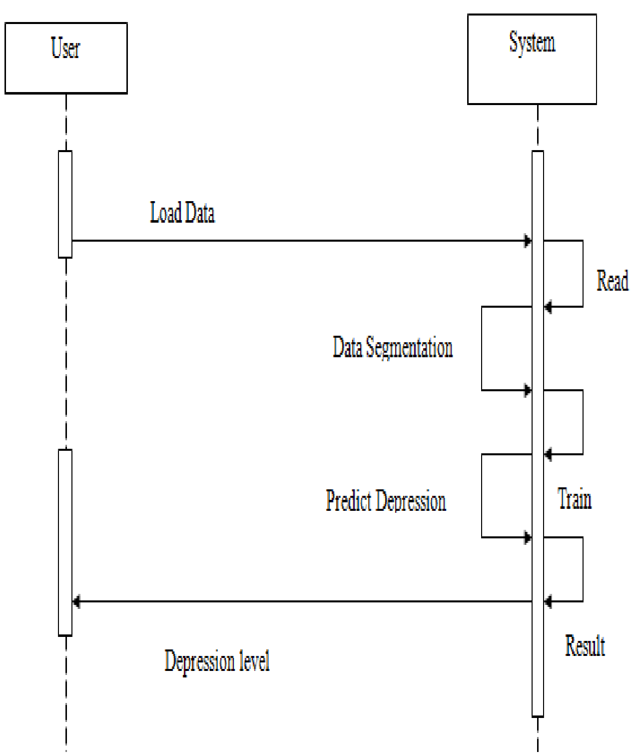

Fig.8: shows sequence diagram

Data Flow Diagram:
Level:0

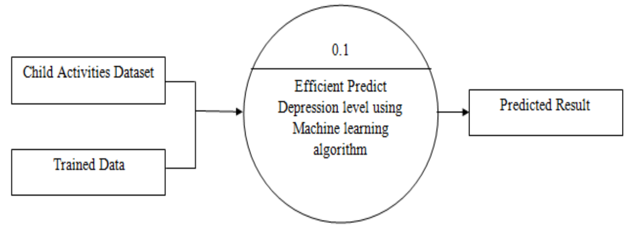

Fig.9: shows Data flow diagram of level-0

Level: 0 describes the overall process of the project. We are passing child activities dataset and trained data as input. By using the machine learning algorithm it will efficiently predict Depression level of given data.

Level: 1

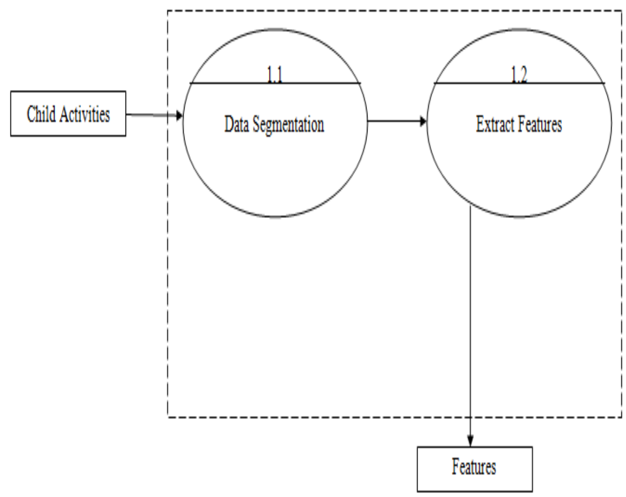

Fig.10: shows Data flow diagram of level-1

Level 2:

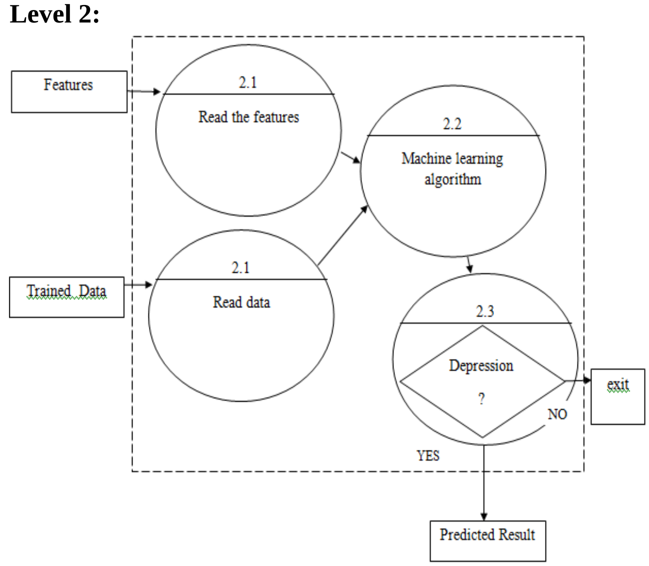

Fig.11: shows Data flow diagram of level-2

VI. IMPLEMENTATION MODULES

1. Data Collection:

To collect these data, child and caregiver were brought into the university-based laboratory and consented to complete a battery of tasks. Caregivers completed questionnaires while children underwent a series of behavioral tasks in an adjacent room with an IMU secured to their waists..

2. Data Segmentation

Data segmented into the three temporal phases described below

Potential Threat: When entering a novel, dimly lit room, the administrator whispers to the child, “There’s something I want to show you in this room.” The administrator then slowly steps forward into the middle of the room, gesturing the child to stand still in front of a covered terrarium.

Startle: The administrator quickly uncovers the terrarium and pulls the fake snake out toward the child at their eye level. The administrator then says, “See it’s fake, you can touch it.”

Response Modulation: The administrator continues holding the snake for the child to see, reassures verbally as needed (e.g., “It’s just a silly toy snake.”), and waits in the room before gesturing the child to leave the room with them.

3. Depression Classification

A supervised learning approach is then used to create k-Nearest Neighbor (k-NN) binary classification models. We establish performance of the classifiers using leave-one-subject-out validation, where we train a k-NN classifier on 59 subjects, and use it to classify the 1 remaining subject as either having an internalizing diagnosis or not, and iterate until each subject has been classified. The accuracy of the classification is computed using the standard formula Accuracy = (True Positives + True Negatives) / Number of Observations. To examine the effect that different feature sets and number-of-neighbors (k) have on classification performance, we compare classification accuracy across a variety of feature sets and values of k. Specifically, we consider kNN models with 1 to 7 neighbors, for each feature set including just accelerometer features (ah, av = ACC), just gyro features (ωh, ωv = GYR), just angle features (α, γ = ANG), and all combinations of those feature sets (7 total).

4. Result evaluation

A scatter plot of the first two principal components of the feature space provided by combining the ANG and ACC features, where a gray dot corresponds to participants with an internalizing diagnosis and black dots correspond to those without. Principle components are computed following conversion of features to their Z-Scores so that each feature has zero mean and unit variance. The classification accuracy for each combination of features and neighbors. Colors closer to white represent good performance while colors closer to red represent poor performance. The best performing models achieve a classification accuracy of 75%, while the worst performing models achieve an accuracy of 55%.

CONCLUSION

The results presented herein demonstrate that, when pairedwith machine learning, 20 seconds of wearable sensor data extracted from a fear induction task can be used to diagnosis internalizing disorders in young children with a high level of accuracy and at a fraction of the cost and time of existing assessment techniques. These results point toward the future use of this approach for diagnosing children with internalizing disorders.

REFERENCES

[1] H. L. Egger and A. Angold, “Common emotional and behavioural disorders in preschool children: presentation, nosology, and epidemiology,” J Child Psychol Psychiatry, vol. 47, no. 3–4, pp. 313– 337, Apr. 2006.

[2] S. J. Bufferd, L. R. Dougherty, G. A. Carlson, and D. N. Klein, “Parent-Reported Mental Health in Preschoolers: Findings Using a Diagnostic Interview,” Compr Psychiatry, vol. 52, no. 4, pp. 359–369, 2011.

[3] M. Tandon, E. Cardeli, and J. Luby, “Internalizing Disorders in Early Childhood: A Review of Depressive and Anxiety Disorders,” Childand Adolescent Psychiatric Clinics of North America, vol. 18, no. 3, pp. 593–610, Jul. 2009.

[4] J. L. Luby, A. C. Belden, J. Pautsch, X. Si, and E. Spitznagel, “The clinical significance of preschool depression: Impairment in functioning and clinical markers of the disorder,” Journal of AffectiveDisorders, vol. 112, no. 1–3, pp. 111–119, Jan. 2009.

[5] D. J. Whalen, C. M. Sylvester, and J. L. Luby, “Depression and Anxiety in Preschoolers: A Review of the Past 7 Years,” Child and Adolescent Psychiatric Clinics of North America, vol. 26, no. 3, pp.503–522, Jul. 2017.

[6] H.-U. Wittchen and H. Sonntag, “Nicotine consumption in mental disorders: a clinical epidemiological perspective,” EuropeanNeuropsychopharmacology, vol. 10, p. 119, Sep. 2000.

[7] A. Bittner, H. L. Egger, A. Erkanli, E. Jane Costello, D. L. Foley, and A. Angold, “What do childhood anxiety disorders predict?,” J ChildPsychol Psychiatry, vol. 48, no. 12, pp. 1174–1183, Dec. 2007.

[8] M. S. GOULD et al., “Psychopathology Associated With SuicidalIdeation and Attempts Among Children and Adolescents,” Journal ofthe American Academy of Child & Adolescent Psychiatry, vol. 37, no. 9, pp. 915–923, Sep. 1998.

[9] M. G. Craske and M. B. Stein, “Anxiety,” The Lancet, vol. 388, no. 10063, pp. 3048 3059, Dec. 2016.

[10] A. Konnopka, F. Leichsenring, E. Leibing, and H.-H. König, “Costof- illness studies and cost-effectiveness analyses in anxiety disorders: A systematic review,” Journal of Affective Disorders, vol. 114, no. 1, pp. 14–31, Apr. 2009.

[11] J. L. Luby, “Preschool Depression: The Importance of Identification of Depression Early in Development,” Current Directions inPsychological Science, vol. 19, no. 2, pp. 91–95, May 2010.

[12] J. L. Luby et al., “The clinical picture of depression in preschool children,” Journal of the American Academy of Child & AdolescentPsychiatry, vol. 42, no. 3, pp. 340–348, Mar. 2003.

[13] J. Garber and K. M. Kaminski, “Laboratory and performance-based measures of depression in children and adolescents,”

Journal ofclinical child psychology, vol. 29, no. 4, pp. 509–525, 2000.
[14] T. E. Chansky and P. C. Kendall, "Social expectancies and selfperceptions in anxiety-disordered children," J Anxiety Disord, vol. 11, no. 4, pp. 347–363, Aug. 1997.
[15] D. J. Kolko and A. E. Kazdin, "Emotional/behavioral problems in clinic and nonclinic children: Correspondence among child, parent and teacher reports," Journal of Child Psychology and Psychiatry, vol. 34, no. 6, pp. 991–1006, 1993.
[16] A. G. Renouf and M. Kovacs, "Concordance between mothers' reports and children's self-reports of depressive symptoms: Alongitudinal study," Journal of the American Academy of Child &Adolescent Psychiatry, vol. 33, no. 2, pp. 208–216, Feb. 1994.
[17] D. Cawthorpe et al., "Priority-Setting for Children's Mental Health: Clinical Usefulness and Validity of the Priority Criteria Score," J CanAcad Child Adolesc Psychiatry, vol. 16, no. 1, pp. 18–26, Feb. 2007.
[18] C. Lord et al., "The autism diagnostic observation schedule-generic: a standard measure of social and communication deficits associated with the spectrum of autism," J Autism Dev Disord, vol. 30, no. 3, pp. 205–223, Jun. 2000.
[19] E. J. Mash and S. L. Foster, "Exporting analogue behavioural observation from research to clinical practice: useful or costdefective?," Psychol Assess, vol. 13, no. 1, pp. 86–98, Mar. 2001.
[20] E. McGinnis et al., "Movements indicate threat response phases in children at-risk for anxiety," IEEE Journal of Biomedical and HealthInformatics, vol. 21, no. 5, pp. 1460–1465, 2017.
[21] N. L. Lopez-Duran, N. J. Hajal, S. L. Olson, B. T. Felt, and D. M. Vazquez, "Individual differences in cortisol responses to fear and frustration during middle childhood," J Exp Child Psychol, vol. 103, no. 3, pp. 285–295, Jul. 2009.
[22] J. J. Gross, "Emotion regulation: Affective, cognitive, and social consequences," Psychophysiology, vol. 39, no. 3, pp. 281–291, May 2002.
[23] R. S. McGinnis, S. M. Cain, S. P. Davidson, R. V. Vitali, S. G. McLean, and N. C. Perkins, "Validation of Complementary Filter Based IMU Data Fusion for Tracking Torso Angle and Rifle Orientation," presented at the ASME 2014 International Mechanical Engineering Congress and Exposition, Montreal, QC, 2014, p.V003T03A052.
[24] R. McGinnis, "GitHub repository," GitHub. [Online]. Available: https://github.com/ryan-mcginnis. [Accessed: 03-Nov-2017].
[25] B. Birmaher et al., "Schedule for Affective Disorders and Schizophrenia for School-Age Children (K-SADS-PL) for the Assessment of Preschool Children- A Preliminary Psychometric Study," J Psychiatr Res, vol. 43, no. 7, pp. 680–686, Apr. 2009.