

# **Smartphone-Based-Suicide-Prevention: Concept Drift Adaptive Classifier-based Detection of Suicidal Ideation During Rehabilitation Using Multi-Modal Feature Data Continuously Acquired from Smartphone Use**

*Note: The breadth and depth of this project, from the design and integration of signal, image and text processing for feature extraction, to development of the proposed classifier architecture and training algorithms, to the process of collecting a database, and most importantly it's application in the rehabilitation setting would require collaboration with an institution having the interest to investigate the use of smartphone-based feature data acquisition and machine learning to address this critical issue affecting both patients and their families. Thanks to Boston Scientific and Vanguard Health, the Connected Patient Challenge has provided an opportunity to raise awareness of this serious problem in the setting of rehabilitation. This submission is simply a proposal made in the hope sparking interest, and hopefully initiating a collaboration to develop and test a system based on these overall principles.*

Recent research indicates a heightened risk of suicide among those who have acquired a physical disability or sustained a traumatic brain injury [57-60, 62-64]. Several quotes from that literature serve to make clear the urgent nature of this problem, and the need for improved solutions to minimize this risk: *"There appears to be about a three to fourfold increased risk of suicide after TBI.", "Recent research indicates a heightened risk of suicide in this population... The suicide rate after acquiring a physical disability, such as a spinal cord injury, and the greater odds of suicide after reporting having a disability further support the association between physical disability and suicide.", and "Research among a wide range of cohorts (e.g. civilian, military) has increasingly highlighted traumatic brain injury (TBI) as a risk factor for suicidal thoughts and behaviors, including death by suicide."*

Machine learning techniques based on large margin perceptrons (e.g., SVMs) are sensitive to task-relevant features and robust to both noise and irrelevant features [8, 10-13]. Such techniques can be applied to the detection of critical points in the psyche of a patient in rehabilitation who is making a sudden movement in the direction of suicidal ideation or suicide attempts. Relevant feature data can be acquired continuously from multiple, relevant smartphone sensors and modalities, and processed by a classifier trained to demarcate the transition from healthy to suicidal patterns of thought and behavior. The use of a multi-scale decomposition of classifier decision boundaries is proposed for a machine learning architecture [2, 3] designed to allow dynamic adaptation to non pathological state variation, while maintaining accurate decision boundary detection that will enable detection of at risk individuals crossing into states indicating suicidal ideation or high risk of impending suicide attempts. This proposed architecture is an extension of the LLDN neural network described in [8], and was inspired by research into the use of localized linear discriminants [8] for optimized adaptation to patients on intensive care monitors while the author was a research scientist at Siemens Corporate Research. The problem of generating accurate alarms for arrhythmias over relatively long periods of time for patients in intensive care, while simultaneously adapting to daily and longer term variations in ECG morphologies which do not correspond to pathologies or events warranting alarms, is seen to be a parallel problem to monitoring someone at risk for suicidal ideation leading to suicide attempts. As nursing staff will shut off alarms from a monitor that generates too many false alarms, so will alarms from a smartphone based suicidal ideation monitor be ignored, or else relegated to a low priority, if that false alarm rate is too high. (Except for the NIPS paper, "A Network of Localized Linear Discriminants" [8], the research applied to ICU/CCU monitoring was neither published nor is protected by IP). In order to optimize both the sensitivity and specificity of suicidal ideation / imminent attempt detection, the multi-scale version of the LLDN (MS-LLDN) will be embedded in a multi-view classifier architecture [4-5, 18], in which each MS-LLDN classifier is trained and operates independently within each smartphone sensor / modality feature space, with each MS-LLDN output ultimately combined in a form of a mixture of experts model. This overall architecture allows alarm generation based on either significant movement towards or across decision boundaries for any single sensor / modality, as well as detection of correlated movements across sensors and modalities.

The capabilities of such a system to be sensitive to short term movements in mental states and behaviors in dangerous directions is critical to the prospect of saving lives. *"A recent review of the past 50 years's of research on the prediction of suicide and suicide attempts revealed that only one-tenth of 1 % of such studies have examined risk factors of the short-term occurrence of such outcomes—that is, what factors predict whether is going to engage in suicidal behavior over the next 1-30 days..."* [1]. Appropriately, interest in the use of dynamic data streams for the detection of impending suicide risk has increased with the availability of smartphones and wearable sensors. *"Related research has noted that most known risk factors for suicidal behavior actually predict suicidal ideation, but not the transition from suicidal thoughts to attempts. As such, there is a great need to identify factors that are the strongest predictors in the weeks, days, and hours before a suicide attempt, new objective markers of short-term risk, the need for new methods to combine these risk factors into actionable predictions..."*. *"Thus, an important first step for new approaches to suicide prediction is the ability to capture novel dynamic risk data of clinical importance. While data gathered in-person by a licensed clinician remains the current gold standard for both healthcare and legal standards, there is now the ability to augment the clinical exam with new, dynamic, and real time data about potential risk factors for suicidal behavior"* [1]. The need for accurate, sensitive detection of someone rapidly moving into dangerous territory is reinforced by this statement: *"As suicide ideation and*

suicide risk change rapidly, access to high quality mobile resources may save lives” [6]. Only a classifier with the ability to adapt to normal variations in mental states, behavior, and affect, while maintaining accurate decision boundaries for detection of rapid movements into self destructive mental states and behaviors will be able to generate alarm signals with an acceptable level of false alarms while keeping false negatives to an absolute minimum.

The acquisition and use of multi-modal data for detection of suicidal ideation allows integration of both higher and lower level features in a classifier, as shown in recent research to improve the ability to predict suicidal behavior. *“In order to overcome this hurdle, it is necessary to analyze a wide variety of behavioral data in a multivariate fashion, often collected from a myriad of sources, in order to make successful short-term predictions. Because of this, data integration is particularly essential for the success of short-term risk prediction”* [1]. *“Unlike existing tools, the model asks adolescents not only about suicidal thoughts but also about other factors that may put them at risk, including sleep disturbance, trouble concentrating, agitation, and issues with family and school connectedness. Different combinations of risk factors can place youth at risk. If we screen only for suicidal thoughts, we will miss some high-risk adolescents,” said lead author Cheryl King, PhD, a professor, clinical child psychologist, and director of the Youth and Young Adult Depression and Suicide Prevention Research Program in the Department of Psychiatry at Michigan Medicine. There are many reasons young people may not share suicidal thoughts, possibly because they’re ashamed, they aren’t experiencing the thoughts at the time of screening, or someone reacted in a way they didn’t feel was helpful when they shared suicidal thoughts or sensitive information in the past”* [9].

The smartphone as a platform is then ideally suited to this task of collecting data across multiple modalities in real time for this application [23-30, 32-35]. Feature data can be culled from a broad range of sources, including:

- Prosodics and other features of speech carrying information about feelings / emotion / affect [38-47]
- Text and email messages (sentiment, content, social connectivity) [36, 67-68]
- Facial expression, eye movements [48-51]
- Heart rate and heart rate variability [53]
- Fine and coarse patterns of movement (GPS, accelerometer, typing rates & rhythms) [52, 54-55, 65]
- Patterns of usage of smartphone apps (types, durations) [37]

Due to close and frequent collaboration with therapists, patients in a rehabilitation setting are particularly accessible, with the potential for great benefit, for collection of potentially relevant feature data. While applications are now appearing for smartphone-based recognition of affect and emotion for commercial purposes, or the delivery of mental health services to the general population [23-30], it is still the case that classifier performance is generally optimized when trained on data from a specific subset of a population with a focused goal. Even when the goal is the use of machine learning to detect suicidal “thought markers”, the full range of modalities with potential to indicate a drift towards suicidal ideation has not been explored as input data to be processed in real time. The goal of this project is therefore the prototyping and training of a binary classifier focused exclusively on patients with recently acquired physical disabilities or TBI in an intensive rehabilitation setting, utilizing the broadest range of potentially useful data available from the smartphone as a data acquisition platform. The focus on this particular group is based on the relatively higher risk of attempted suicide and the frequency of interaction with therapists. This unique environment would be an extremely effective way to collect and label the data, and develop the classifier and the overall application in a relatively fault-tolerant setting (due to the level of patient supervision). In addition to providing a dataset (appropriately anonymized) for further research and development by experts in this field, the intended product would be a free smartphone application for use by professionals in rehabilitation and patients wishing to take advantage of the potential benefit of such a system. Once efficacy is proven, this capability could be extended to a wider range of settings. The use of the technique for optimized synthesis of classifiers for new patients [3] would be used to initialize the system for each new patient, based on a minimal amount of baseline training data; at that point each smartphone would be patient-specific, and adaptive in an online learning fashion. Thus a focused data collection and development effort would potentially have a wider range of application to other sub-populations at risk, such as teenagers, the elderly, and those sustaining significant changes on the life events scale.

The analysis of fine grained data in the time domain is both critically important, and little studied to date [66, 69-70]. From [1]: *“Short-term risk prediction is a more difficult problem due to the necessity of inference based on a small amount of data, which means that meaningful signals can more easily be lost due to noise from highly variable behaviors.” “However, prospective comparisons of machine learning tools to predict short-term suicide risk have not yet been conducted, despite the tremendous potential. In part, this is because the short-term risk factors derived from social media and smartphone are still not well characterized or validated. Crucially, even the best computational methods for risk assessment will only ever be as good as the risk factor data provided to them. Thus improvements in smartphone and sensor data quality are critical for realizing the full potential of new machine learning methods operating with this data.”* This proposal to embed the data collection / classifier platform in a rehabilitation setting with relatively continuous interaction with therapists would be a significant step to address the problem of collecting data on short-term risk, as the level of short-term risk can be verified by therapists on a fine-grained temporal basis, enabling the training of a classifier to detect short-term movements in feature space in a direction of immediate or short-term risk. The importance of obtaining high quality clinical data for classifier training is critical due to the cost of false negative alarms in this application, and from [1] it is clear that there is clearly the need for this type of data, and smartphone based machine learning trained on this data: *“However, the*

*evidence today suggests that current smartphone apps targeting suicide on the commercial market-places including the Apple App Store and Google Play store are largely not evidence based and few have been clinically validated”.*

The limitation to binary classification is done to limit classifier complexity, make best use of the training data as it is acquired for this new database, and most importantly to focus exclusively on the task of detecting indications of suicidal ideation and/or behaviors indicative of imminent suicide attempts. The two classes will nominally represent categories like “well” and “marginal”, in order to generate a conservative decision boundary for initiation of earlier, more intensive therapist interaction, so as to intervene as early as possible in a patient’s potential path towards a suicide attempt. Optimized use of the initially limited amount of training data will also be the result of using each distinct type of feature data (text, speech, facial expression, patterns of movement, heart rate, etc.) independently with sub-classifiers that act as “experts” for each type of feature data in a multi-view architecture approximating a mixture of experts model. Again, from [1], the statement: *“In order to overcome this hurdle, it is necessary to analyze a wide variety of behavioral data in a multivariate fashion, often collected from a myriad of sources, in order to make successful short-term predictions. Because of this, data integration is particularly essential for the success of short-term risk prediction”*, supports the use of a multi-view based architecture in this application, allowing detection of movements in each individual feature space (associated with each distinct type of data) both independently of other data types, as well as integration of correlated movements across individual feature spaces [4]. This not only limits the trainable complexity of the overall classifier, improving generalization performance, it allows each expert / sub-classifier to function independently of the others – since, in the general case, the input modalities will be active at disjoint times. This particular variant of the mixture of experts architecture will also utilize integration in the time domain, allowing an alarm for therapist intervention to be generated from either a single sub-classifier (e.g., detection of what appears to be a suicide note sent by text or email or simply composed in an editor), or more subtle cues distributed across several input modalities, integrated over a sliding window in time.

Several types of data are available for classifier training – results of ongoing mental health assessments (which can also be smartphone-based, both patient and therapist initiated), in person therapist assessments, and actual suicide attempts. Graded results from assessments can be used to give partial weight to feature vectors associated with both healthy and unhealthy states for classifier training. As the rate of successful completion of suicide attempts is low, attempts serve as distinct ground truth labels for feature vectors that are closest to the attempt in time and would be labeled with full weight. In order to provide utility to both patients and therapists in the earliest phase of this project, prior to the collection of sufficient data to initiate classifier training, the classifier in its untrained form will operate as an outlier detector, simply using an isotropic decision boundary for each sub-classifier and for the overall output of the mixture of experts as well to detect significant departures from baseline behavior in any direction. This will be a bootstrapping process, as training data is acquired and the classifier is incrementally trained resulting in a transition to discriminative, task-relevant decision boundaries composed of a mixture of localized large margin / soft margin linear discriminants. The higher level of risk for this patient population, combined with frequent interaction with therapists, will provide for relatively rapid bootstrapping of the classifier. The final threshold of this ensemble classifier, defining the detection of “potential suicidal ideation/action,” would be adjusted to err on the side of caution and early intervention in all phases of the evolution and operation of the classifier.

Growing awareness in the machine learning community of the problem of classifier adaptation to concept drift / distribution shift elevates the ability of a classifier to track dynamic changes in data distributions in order to maintain accurate decision boundaries between classes of data [7, 14-16, 56]. In this application, the decision boundaries are between states of mind not immediately of concern with regard to suicidal ideation and attempts, and those that indicate a boundary has been crossed to a state of mind putting an individual at short-term or immediate risk for suicide attempts. As non-pathological states of mind, and behaviors, are constantly shifting over the course of a day, as well as longer time windows, it is necessary to dynamically adapt to those shifts in order to maintain classifier performance. For example, *“It turns out,” Ng said, “that when we collect data from Stanford Hospital, then we train and test on data from the same hospital, indeed, we can publish papers showing [the algorithms] are comparable to human radiologists in spotting certain conditions.” But, he said, “It turns out [that when] you take that same model, that same AI system, to an older hospital down the street, with an older machine, and the technician uses a slightly different imaging protocol, that data drifts to cause the performance of AI system to degrade significantly.” (IEEE Spectrum, May 3, 2021, “Andrew Ng X-Rays the AI Hype”).* Beyond the example of impact of increased error rate in an important application like diagnostic radiology, the cost of increased error rate in suicidal ideation detection is incalculable.

Machine learning techniques appropriate to concept (pattern) drift will be applied to develop a user-adaptive classifier that tracks gradual shifts over time, allowing optimum detection of periods in time when intervention is advisable. A properly tuned adaptive classifier should be capable of dynamically following cyclical shifts in mood and topics of concern that are typical, and not indicative of a drift towards a pathological state, while at the same time being capable of detecting sudden shifts in a pathological direction; this sensitivity is critical due to the relatively impulsive nature of many suicide attempts. This is a distinct variant of the mixture of experts model using adaptive localization functions to track concept drift independently in each feature space. Each sub-classifier will also utilize wrapper-type bootstrapped cross-validation for feature selection using features extracted, where appropriate, from deep scattering networks. The use of deep scattering networks for feature extraction allows the evaluation of multi-scale wavelet features over multiple layers of wavelet analysis, in a front-end architecture similar to that of trainable deep networks. The advantages of deep scattering networks

in this application are the fact that they are overcomplete transforms (important for classification) requiring no training (minimizing the need for very large databases) and are partially invariant to affine transformations of the data (necessary to process data like speech and facial images). Each “expert” sub-classifier is essentially self-gated due to the localization functions, only contributing to the ensemble output when a particular feature type (i.e., speech, text, etc.) is in a meaningful region of that feature space. A classifier using static decision boundaries will be one additional component of the ensemble, providing a back-up system for detection of consistent longer-term drifts towards dangerous psychological states.

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