Mission Daybreak
U.S. Department of Veterans Affairs

July 8, 2022

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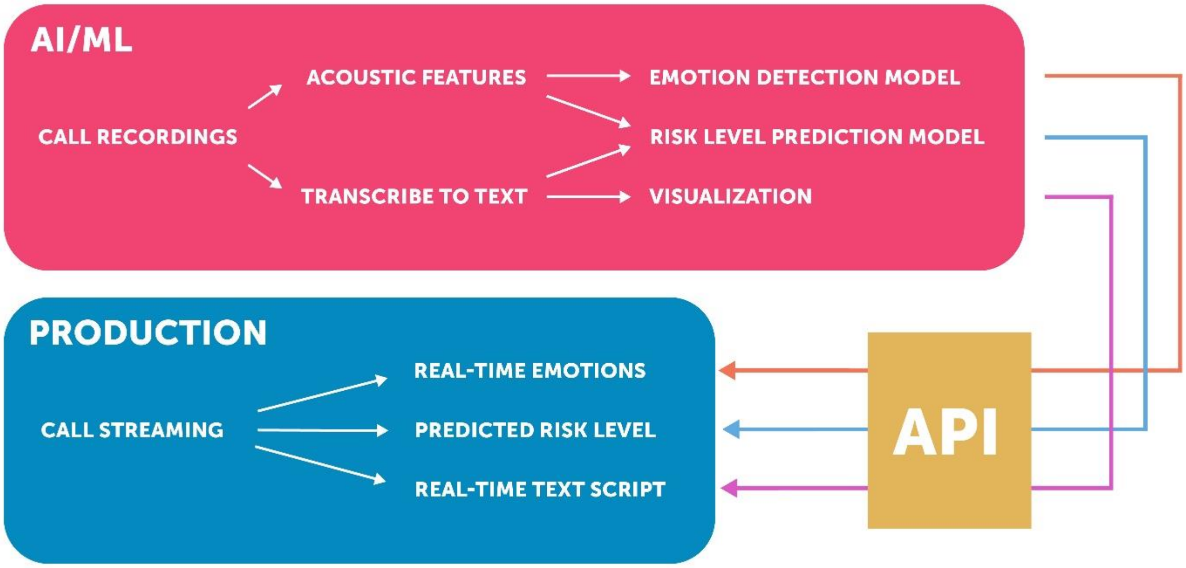
Document Storage Systems, Inc. (DSS) is pleased to provide our response to the Mission Daybreak Challenge. We are confident our submission meets the requirements of the request and demonstrates the required technical skills, experience, and personnel to meet all requirements. No federal funds were used in the development of this proposal.

1. Solution description. High-level description of the proposed solution, its intended impact, rationale for efficacy, and how it can be implemented.

According to the 2021 National Veteran Suicide Prevention Annual Report, there were 6,261 Veteran suicides reported in 2019. That is 6,261 too many. In response to this crisis, the June 6, 2022 Department of Veterans Affairs Office of Inspector General (OIG) report on Suicide Prevention recommended improved training, guidance and improved performance metrics to increase opportunities to assist Veterans at risk of suicide. In addition, the launch of the new 988 three digit dialing code, while a positive development to help potentially reduce Veterans suicide, is underfunded and sure to increase call volume and potentially overwhelm Veteran Crisis Line (VCL) operators. This could over-stress the VCL system and risk losing callers who may be experiencing suicidal thoughts. The solution we propose aims to solve these problems by using Artificial Intelligence (AI) and Machine Learning (ML), using data from both active and passive sources to more effectively assist operators in triaging Veterans calling the VCL. Operators will have the ability to provide the most appropriate services to each Veteran and increase operators' ability to manage a higher call volume and triage more calls.

Our Solution

Our solution is a multidimensional approach to detect suicidal ideation in real-time using Machine Learning (ML) techniques. There is a significant amount of data available from inbound calls to the VCL that can be analyzed to better understand suicidal ideation expressed by callers and predict the risk of suicide and / or suicide attempts. Operators are often overwhelmed with the number of calls and need tools to assist them in assessing Veteran's suicide risk level in real-time. The prediction accuracy obtained by current ML techniques is around 80% [Belouali, A., Gupta, S., Sourirajan, V. et al., Acoustic and language analysis of speech for suicidal ideation among US veterans. BioData Min. 2021 Feb 2;14(1):11.] which could be further improved through innovation. The multidimensional approach we propose uses explainable ML, which is an algorithm created using scientific knowledge in a process that can be explained. Explainable ML algorithms are ethical and trustworthy because we can explain how they work. This ML algorithm detects emotion and/or stress in the caller's voice in real time by analyzing acoustics, voice level, speed and pauses in the conversation. The resulting distress prediction is viewable by the operator during the call. In addition, voice is translated to text and analyzed with ML using Natural Language Processing (NLP) to provide further accuracy in prediction. Meaningful and actionable insights obtained from this functionality provide valuable learning opportunities, which can be used to not only make data informed decisions, but also for training purposes. Our proposed solution would further improve the prediction accuracy rather than using voice or text independently. The final ensembled model will be integrated with the Medora system to provide real-time risk level prediction to help operators assess and triage calls and take appropriate action.



Additional Insights from Data

Data from the Veteran's service and medical record located in VistA is also valuable and can be used to provide a more accurate picture of risk when combined with results from the call data, using both active and passive data, both present and historic data. Information on mental health diagnoses including PTSD, substance abuse, previous suicide attempts, physical ailments, military experience, prescribed drugs, employment, and marital status could all impact a Veteran's risk level. Therefore, the information obtained from the calls along with the Veteran's service and medical record data available on VistA can also help provide a better understanding of suicidal risk. We would like to explore opportunities to work with any systems VA is currently using, such as the Suicide Prevention Applications Network (SPAN), and /or to coordinate with collaborative government agencies in this arena such as Interagency Collaboration for Advancing Predictive Analytics (ICAPA) or the Oak Ridge National Laboratory (ORNL) to maximize data and if appropriate to refine and update existing suicide risk prevention models or create new tools for predicting suicide risk.

An additional and important element of the implementation of Phase II of this process will be to identify key non-clinical data elements within VistA that can be used to help determine the Veteran's risk of suicide. DSS will leverage its vast experience developing APIs for VistA to create APIs to pull Veteran data from VistA into the AI/ML engine in areas such as disability ratings, disability determination status, VA home loan payment status, etc. These non-clinical data elements are important for a number of reasons. For example, if a Veteran has received a high disability rating in the past, then we can determine the extent to which they will be facing disability-related challenges. If they have recently received a disability determination or have recently been denied a disability rating, then these come with their own set of stressors. If we can tell that the Veteran is behind on their mortgage payments, then we can determine their risk of becoming homeless and the impact that this has on their mental health.

One of the most effective ways to improve precision and speed of call response is to continually track and measure the results of our actions. The OIG report included the recommendation to improve performance metrics to increase opportunities to assist at-risk Veterans. Improving performance metrics would be based on existing systems. If the metrics currently exist, then creating reports for the appropriate audience and developing thresholds and resulting actions for the metrics would make the data useful and actionable. If measures are not currently being taken, then we can create them, developing Key Performance Indicators (KPI's) and establishing thresholds and related actions based on the results, to fulfil the recommendation from the OIG.

Ethics in AI Training

A comprehensive solution using AI and machine learning is more effective when leaders, practitioners and users understand AI's ethical and accountable implications. In fact, solutions to address mental health and suicide will have a positive impact only if there is trust and accountability in the development and implementation of AI, especially with respect to cases involving human emotion and behavior modification. If that trust cannot be established it will be difficult to impossible to effectively and efficiently serve the Veteran population, which spans a multitude of generations, varied socio-economic status and the full spectrum of diversity.

We know that the federal government, and the VA in particular, is embarking upon developing and implementing AI solutions within the context of trustworthy AI. As such, it is essential for any initiative affecting the Veterans population consider and implement trustworthy AI initiatives, from ideation and design through AI implementation and feedback. Moreover, VA leaders and staff should be adequately familiarized with AI methods, then trained and prepared to operate in a collaborative and trustworthy AI environment.

AI trust starts with leadership, and AI familiarization should inform and prepare managers and leaders to adopt AI strategically, responsibly, and thoughtfully within the context of ethics, transparency and accountability. We have included in our solution an application to do just that. The Artificial Intelligence Learning Platform System (AILPS) is an application that provides self-paced, trustworthy AI training for managers and leaders. We cover five essential categories that include AI familiarization of terms and concepts; AI data and data set management techniques; ethical and trustworthy AI implications; considerations for selecting the right AI platform that best conforms to VA use cases such as an AI integrated VCL application; and finally optimizing human talent and effectiveness with the proper alignment between machines and employee teams. We tailored the training to focus on real world use cases, and cover the ethics of AI creation, development and deployment.

To include a greater percentage of VA Leaders trained in AI ethics and management principles, we have devised our AI training in such a way that it is self-paced and takes a little over an hour to complete. Indeed, our AI training procedure for trustworthy AI can be used for certification that ensures an increased number of VA staff have access to certifiable AI ethics training. Essential to the VA achieving and optimizing AI readiness is to ensure that leaders are addressing use cases and overseeing AI solutions with sound AI management principles within the context of ethics, responsibility and legality. We achieve these goals with our AI-focused training and believe it is vital to any solution involving an AI use case such as mental health and addressing issues of Veterans suicide.

Finally, with the broader implementation of AI and ML use cases in VA, it is important to consider engagement and collaboration among the broader Veterans community. Imbuing the general VA population with a trustworthy and ethical AI framework assures a myriad of important milestones in the creation of an AI ready organization, to include building and growing collaborative interoperable AI teams to drive culture change and fast track AI adoption; accessing AI assets to facilitate sharing and continuous learning; empowering community members to create and innovate using the latest AI tools; and maximizing human to machine teaming to ignite innovation and effectiveness.

2. Veteran impact. Detailed description of intended audience (for example, a specific Veteran group, region, or context), and how the solution works for these users.

In 2007, the Veterans Health Administration (VHA) established the National Veterans Suicide Prevention Hotline, now known as VCL, in response to the Joshua Omvig Veterans Suicide Prevention Act, Public Law 110-110. The act mandated that VHA provide mental health services 24 hours per day, seven days per week, and a toll-free hotline for Veterans. Since established, VCL reports that staff have answered more than five million calls, engaged in more than 606,000 chats, and responded to more than 193,000 texts. VCL staff refers individuals to local VHA mental health services, as appropriate. VCL centers are located in three sites: Canandaigua, New York; Atlanta, Georgia; and Topeka, Kansas. VCL, aligned under the Office of Mental Health and Suicide Prevention, is accredited by the Commission on Accreditation of Rehabilitation Facilities (CARF).

The VCL is a toll-free, confidential resource that connects Veterans in crisis and their families and friends with qualified, caring U.S. Department of Veterans Affairs (VA) responders. Veterans and their loved ones can call 1-800-273-8255 and Press 1, chat online at VeteransCrisisLine.net, or send a text message to 838255 to receive free, confidential support 24 hours a day, 7 days a week, 365 days a year, even if they are not registered with VA or enrolled in VA health care.

The VLC's new number—988 then Press 1—helps make it easier to remember and share the number to access help in times of need. Signed into law in 2020, the National Suicide Hotline Designation Act authorized 988 as the new three-digit number for the National Suicide Prevention Lifeline. All telephone service providers in the U.S. must activate the number no later than July 16, 2022. It is expected that this new number and the public service announcement campaigns designed to raise awareness, will significantly increase calls to the VCL.

The responders at the Veterans Crisis Line are specially trained and experienced in helping Veterans of all ages and circumstances — from Veterans coping with mental health issues that were never addressed to recent Veterans struggling with relationships or the transition back to civilian life. Moreover, we devised our solution to more accurately assess our underserved, at risk Veterans who are often hard to reach and convey their emotions and stress with different verbal and written cues. VCL responders provide support when these and other issues — such as chronic pain, anxiety, depression, sleeplessness, anger, and even homelessness — reach a crisis point. Some of the responders are Veterans themselves and understand what Veterans and their families and friends have been through. A state-of-the-art AI/ML solution that: automates tasks; elicits additional potential life saving information from callers; improves efficiency and effectiveness; harmonizes and coordinates data collected during the call; and links those in urgent need to immediate care within the Veteran community, will greatly improve care and coordination for the Veteran in crisis.

3. Evidence framework. Demonstration of evidence-based or evidence-informed decision-making in developing this solution, as well as a framework for defining success, including any relevant citations needed.

DSS, Inc. uses an evidence-based process which includes applying current scientific evidence, Veteran/patient perspective and clinical expertise, combined with trustworthy/ethical/responsible AI practices to make decisions regarding healthcare applications. We reviewed numerous scientific research papers on Emotion AI concluding this to be a promising technology for identifying emotions and suicide ideation. We have also met with several companies selling Emotion AI technology for the purpose of fraud detection or sentiment analysis. Bringing this technology to healthcare is the next logical step, and several research papers have documented the value in doing so, including: [Bone D, Lee CC, Chaspari T, et al. Processing and Machine Learning for Mental Health Research and Clinical Applications. IEEE Signal Processing Magazine [Perspectives] 2017;34:189–95] and [Pestian JP, Grupp-Phelan J, Bretonnel Cohen K, et al. A Controlled Trial Using Natural Language Processing to Examine the Language of Suicidal Adolescents in the Emergency Department. Suicide Life Threat Behav 2016;46:154–9] as well as the study of Acoustic and language analysis of speech for suicidal ideation among US Veterans mentioned in section 1 above, second paragraph.

In addition, while researching this project we reviewed the 2021 National Veteran Suicide Prevention Annual Report (September 2021), the OIG Report on Veteran Suicide Prevention (June 6, 2022), The National Strategy for Preventing Veteran Suicide, and more. Although many steps have already been taken by the VA to prevent Veteran suicides, several needs emerged from these documents including the need for improved training and guidance for Suicide Prevention Coordinators and improved performance metrics from the VCL to increase opportunities to assist at-risk Veterans. The VCL is a very important link to and for Veterans, giving VA the opportunity to interact with Veterans in crisis and provide services or intervention according to need. Concerns about the impact of the 988 line on the VCL need to be addressed to reduce the risk of losing callers who may be experiencing suicidal thoughts.

Clinical expertise and Veteran experience were utilized to further understand these needs. Experts in trustworthy/ethical/responsible AI and ML provided solutions based on their research that is expected to increase efficiency in triaging VCL calls, matching callers to appropriate services, fulfilling their needs, and providing more data to drive data driven decisions toward further reducing Veteran suicide levels. We also focus on explainable AI, ensuring that the process and methods we use to generate AI/ML allow users, Veterans, their families and the community to understand and trust the results. Explain-ability is important to our organization in building trust and confidence in our AI models.

Measures taken before implementation and after will be compared to validate success or provide information for further improvement. Continuing iterations will provide continual improvements based on the results of the metrics and related actions. Metrics will cover both validation of the trained Machine Learning algorithms, and operational metrics to track improvements in quality and quantity of services provided by the VCL and staff, including Veteran experience.

4. **Implementation plan. Outline for implementation of the solution, which could include how the solution would integrate with VA or other healthcare systems, scale, or attain community involvement, and outline how the solution plans to mitigate any potential risks and barriers.**

As the proposed solution is AI/Machine Learning driven, data collection will be the first step in the implementation plan. The call recordings collected at VCL and the risk level records in the Medora system will be used as input data for ML model training and testing. Data will be cleansed, and the outliers will be removed based on the nature of the provided data. Then the audios will be analyzed to extract voice characteristics including prosodic, phonation, glottal, Mel-Frequency cepstral coefficients, chroma, and so on. These features will be selected and used as predictor variables. To detect emotions from voice, the target variable will be the emotions which will be evaluated by a clinician by listening and evaluating the call recordings. Then various machine learning techniques will be used to build and test the prediction model, including Support Vector Machine, Deep Learning networks such as RNN, CNN, LSTM, etc. The classifiers will be evaluated by common multiclass classification metrics, such as precision, recall, F1 score, ROC score, Cohen's kappa, etc., and the best performed classifier will be chosen and saved as the model to detect emotions from calls.

To provide an integrated efficient operator workflow, we propose the solution be integrated with Medora, the current information system used by operators at the VCL. Medora would initiate the Application Programming Interface (API) connection / call when a new record for a call is created. This workflow would provide the identifiers and the requisite information needed to match up the related audio stream; note the specifics of this would be finalized in the implementation planning with specific additional knowledge of the telecommunications infrastructure in place. Upon initiating this session, in real time, the solution would return a risk score which would update at intervals into the call (i.e. after the first 30 seconds, at every 30 seconds thereafter for the duration of the call). This information would be presented to the operator in the Medora graphical user interface (GUI) in which they are charting the call providing a cohesive, efficient and integrated experience.

Meanwhile, the call recordings will be also transcribed to text by speech-to-text engines. As there are available products with good accuracy on the market, the team will choose either Google, AWS, or Microsoft to perform this job. The transcribed text features will be used as an additional dimension to predict suicide risk level. Another dimension is the features extracted from call recordings in the previous step. The target variable will be the risk level recorded in the Medora system. The team will perform feature engineering to select best combination of features, explore various machine learning algorithms including Natural Language Processing (NLP) techniques such as Bert and Spark NLP, and examine a single model by voice or text, or a weighted model by the combination of a single voice model and a single text model, to improve classification accuracy. Similar to the emotion detection model described above, the classifier with the best performance will be selected and saved as the model to detect risk levels from calls.

The two models, emotion detection model and risk level prediction model, developed in house will be hosted in a cloud and deployed as an API service. Either AWS, Azure or Google Cloud will be selected to perform this job in the implementation. Depending on the specific commercial cloud, the steps of deployment of machine learning model are different but the core processes are similar, including saving trained machine learning models, creating the docker image, pushing the models to cloud storage, configuring and creating the cloud endpoint, and creating the API endpoint for Medora use. As described above, speech-to-text will be performed by a selected commercial API with no need to train and build a separate machine learning model. Therefore, three APIs will be called in production (hosted in the cloud), fed call streaming data and return corresponding results via API to the Medora system.

For the Medora system and telecommunications infrastructure integration, a development sandbox and testing environment, each which would include a test instance of the telecommunications system (audio feed source) and a test Medora instance, will be required. This will permit development and quality assurance testing. If Medora documentation and that for the telecommunications infrastructure does not provide sufficient information for integration, further help from the respective vendors may be needed for completing integration with the team's solution. As the nature of Mission Daybreak, project integration sandbox, demo sandbox, testing environment sandbox and production environment sandbox are not required at Phase 2.

The implementation of our AI/ML solution would be done in a phased approach. The first phase would involve selecting a test site from among the three VCL centers. Once the appropriate site has been selected, we would prepare this site for User Acceptance Testing (UAT). UAT involves having selected users participate in use case scenarios where they utilize the test environment-deployed software to identify any issues prior to release to a production environment. The results of the UAT testing are gathered and used to make further refinements in the software until users accept the software as ready for operational usage on a daily basis. The second phase implementation would then involve deploying the solution to the other two remaining VLC locations. Additional VistA data elements such as those described in Question 1, will be identified in Phase II and implemented after the finalization of the VCL interface for the AI/ML engine.

With the additional insight of AI/ML, identification of suicide risk for a Veteran will occur sooner than through using just the Medora system. By identifying suicide risk earlier, we will be able to engage community resources earlier to help the Veteran reduce their risk of suicide. We would be able to engage family members and community resources earlier in the process, thus helping reduce the risk of suicide by the Veteran. Family and community involvement is a critical component of reducing suicide risks and improving overall mental health status. We also recognize the value and importance of educating the broader Veteran community about employing this type of trustworthy/ethical/responsible AI approach to suicide prevention to ensure transparency and build trust in support of this effort. We want and need the broader Veteran community – which includes organizations supporting Veterans and their families - to be familiar and assist with this critical work so that all stakeholders are in support of the proposed approach. The opportunity to use technology to prevent suicide is significant but will only succeed if those we seek to serve feel certain about our intentions and safe regarding the use of their personal information.

Potential risks and barriers to implementation are reduced significantly by the way we are gathering data and the fact that no PHI is exposed to the VCL end user during this process. The way we are gathering data is via a set of APIs that will be developed by DSS, who has developed over 40% of the VistA APIs in use at VA. DSS is considered to be the "VistA Experts" within the Healthcare IT community and our knowledge and experience will greatly reduce the risk of these APIs to Medora creating any issues upon implementation. Secondly, risks and barriers are greatly reduced by having all VistA PHI and PII being fed directly to the AI/ML engine for processing behind the scenes and not exposing any of this information to the end user. The AI/ML engine does not have a graphical user interface (GUI), so individuals cannot log in and see the data that is being processed by the engine. The end user only sees the determination of suicide risk on their screens in Medora, not the data that informed the decision.

5. **Needs identification. As an extension of the implementation plan, each submission must include a description of any additional resources the team would need to develop and scale their solution, including a focus on addressing system barriers to implementation.**

The input data used to train machine learning models is the call recordings collected at VCL along with the risk level recorded by responders in the Medora system. The risk level record needs to match the caller of the call recordings, and it will be used as the target variable in machine learning. It is possible that the risk level the responder selected from the dropdown list in Medora system was not appropriate, or if risk level record from Medora system is not provided in this task, then an experienced mental health professional is required to assess and evaluate the risk level from the call recordings. The team has the capacity to provide expertise to evaluate and verify the risk levels, and make sure that will be consistent with the call recordings.

There are concerns of using synthetic call recording data rather than original data. As the core solution in this proposal is to use AI/Machine Learning techniques, using synthetic data would trigger an echo chamber effect, whereby AI generated synthetic data feeds the AI to build machine learning models. Consequently, the AI models that detect and predict key aspects of the Veterans' emotions may increasingly respond to an internal logic unassociated with the real world. In addition, synthetic data can reproduce patterns and biases from the data from which it is generated, and even amplify biases. Different from numerical and text data, synthetic voice data may further increase these discrepancies. Indeed, we have yet to fully understand machine learning efficacy for synthetic voice data. Therefore, the original call recording data is preferred to perform this work by the team. Under the circumstances in which data is synthetically generated, our team plans to incorporate metrics to evaluate synthetic data, including statistical, likelihood, detection, machine learning efficacy metrics for single tables.

Beyond call recordings, the literature indicates that electronic medical records, Veteran residential demographic data, data from public records such as legal, financial, criminal, posting data on social media, and surveillance of data from phone apps and wearable devices, are potentially useful information for predicting suicide risk. This data is not the focus of this task, however, the prediction accuracy could be improved with these additional data resources. It would be good to reference that these additional data sources could be explored during Phase 2 of the challenge – in order to determine if or when they should be included in this model. The team will explore various machine learning algorithms to predict the risk level from call recordings. The supplemental data would provide extra dimensions and potentially additional predictors to the framework described in our submission. If the additional data is synthetically generated, the team would have the synthetic data evaluation metrics for single table and parent-child detection metric for multitables.

Once the call recording training dataset is provided, real-time voice emotion detecting, voice to text transcribing, and risk level machine learning model building can be conducted in house under team's development environment. All training data would be handled consistent with the Health Insurance Portability and Accountability Act (HIPAA) and other Federal privacy and security regulations pertaining to protected health information. As an alternative to providing the voice recordings, the recording data set can be retained / stored / hosted within the VA and made available for training via a secure read only connection. As another alternative, all model training can be carried out within the VA. All personnel will undergo any required VA vetting and background checks needed. Once model training and validation is complete, the trained models will then be deployed. The trained models can be hosted in the cloud and made available as an API for use by the solution.

The solution, which would also run in this cloud environment, would receive the audio stream, operator identifier, and patient identifier(s). The patient identifiers would be used to query for and receive back any requisite patient inputs, for example VistA data or other, should any be included in the final trained models. The solution would then use this data and the trained models to generate the risk scores. To fully develop and scale this innovation DSS, Inc. plans to collaborate with other entities, including the VA and its existing systems, and partner companies. Capabilities research has been completed on several companies that fit gaps and have the potential to increase functionality and performance. Partners will be announced in phase two of Mission Daybreak.

6. Team description. A description of the team, including each person's area(s) of expertise, as well as Veteran status, if applicable.

The DSS team has a wealth of knowledge and expertise between our team members necessary to successfully achieve our proposal. The DSS team members include the following:

- David LaBorde, M.D., M.B.A. is an experienced physician, technologist, inventor and healthcare software company executive. Dr. LaBorde has been granted more than 30 U.S. patents, a significant number of which are for technologies in the artificial intelligence, machine learning (AI/ML) and data science space, including patented AI/ML technology focused on suicide prevention. He is currently the CEO of Iconic Data Inc., a healthcare technology company with solutions focused in the areas of suicide prevention, real time analytics, patient flow optimization, and care coordination. Iconic Data Inc. is an Atlanta Metropolitan Area based company that has been previously recognized as a "Game Changing" health care company by Inc. Magazine. Iconic Data's software is relied upon by U.S. Department of Veterans Affairs Medical Centers within several Veterans Integrated Service Networks to improve patient safety, maximize access to care, streamline complex workflows, and deliver highly reliable care for our nation's Veterans. Dr. LaBorde is also a Senior Clinical Advisor for DSS, Inc., a software products and services company that has worked with the U.S. Department of Veterans Affairs for more than 30 years. Dr. LaBorde has more than 25 years of experience in healthcare and technology and has worked with healthcare provider organizations helping them with strategy, workflow standardization, achieving transparency into their operations, and improving their quality of care and operating performance. He has an M.B.A. from Harvard Business School, an M.D. from Yale School of Medicine, a B.S. in Engineering from Georgia Tech and a Georgia Medical License.

- Barbara Van Dahlen, PhD, is a Licensed Clinical Psychologist, a nationally recognized Mental Health Consultant and a Senior Advisor to DSS. She received her Ph.D. in clinical psychology from the University of Maryland in 1991 and has 30 years' experience in mental health service delivery and national mental health policy. Dr. Van Dahlen is the former Executive Director of PREVENTS (The President's Roadmap to Empower Veterans and End a National Tragedy of Suicide). Concerned about the psychological impact of the wars in Iraq and Afghanistan on Veterans and their families, Dr. Van Dahlen founded the national non-profit organization Give an Hour in 2005 to provide free mental health care to those who serve. She served the organization as President until 2019 when she agreed to build, and lead PREVENTS.
- Xiupeng Wei, Ph.D., is a Data Science Consultant in DSS Inc. Dr. Wei graduated with a degree in Industrial Engineering from the University of Iowa. His expertise and interest are data analytics, AI/machine learning and mathematical optimization. Since graduation he has been working as a data scientist to develop data-driven and AI solutions in energy and healthcare sector. His research has been widely recognized and published in top ranking journals such as Energy and Engineering Applications of Artificial Intelligence. He has successfully developed a two-level stacking algorithm to monitor wind turbine health and predict component failure which achieves remarkably high accuracy after deployed in production. His work therefore was awarded the Finalist Industry Paper Award in 2020 IEEE Prognostic and Health Management Conference.
- Michele Burst is the Director of Strategic Innovations, Analytics at DSS, Inc. bringing her passion for emerging technologies and AI to the organization. Ever cognizant of the opportunities for analytics in Healthcare Technology she completed the Harvard Business Analytics Program and is now bringing that knowledge to DSS through advanced AI. She is also a Lean Six Sigma Master Black Belt and has experience in enterprise-wide endeavors in strategic planning, change management and process improvement.
- Richard Falls has over 25 years of experience in the Healthcare IT field and possesses a Master's Degree in Health Administration from the Medical College of Virginia. He serves as the Solutions Architect for DSS, helping DSS define solutions to some of Healthcare IT's most challenging problems. Mr. Falls has supported the VA for the last 12 years, with prior experience with the Department of Health and Human Services (HHS) and the Defense Health Agency (DHA). He is driven by the belief that IT can continue to transform the delivery of healthcare, resulting in better clinical outcomes and improved services for Veterans and their families.
- Robert L. Gordon III is the Chief Growth Officer of SBG Technology Solutions where he leads SBG's growth and strategy portfolio in emergent technologies such as Artificial Intelligence/Machine Learning (AI/ML) and Cyber Security. As a former Deputy Under Secretary of Defense for Military Community and Family Policy in the Department of Defense, Mr. Gordon's portfolio included overseeing non clinical health solutions for over four million military active duty service and family members. He sat on the VA/DoD Joint Executive Council to address issues of PTSD, mental health and suicide prevention, and for his DoD service was awarded the Secretary of Defense Medal for Outstanding Public Service. He's a former special assistant to three Secretaries of Veterans Affairs. Mr. Gordon's education includes holding an MPA from Princeton University, where he specialized in health policy.

Core solution: Our solution is a multidimensional approach to detect suicidal ideation in real-time using Machine Learning (ML) techniques. This ML algorithm detects emotion and/or stress in the caller's voice in real time by analyzing acoustics, voice level, speed and pauses in the conversation. The resulting distress prediction is viewable by the operator during the call. In addition, voice is translated to text and analyzed with ML using Natural Language Processing (NLP) to provide further accuracy in prediction. Meaningful and actionable insights obtained from this functionality provide valuable learning opportunities, which can be used to not only make data informed decisions, but also for training purposes. Our proposed solution would further improve the prediction accuracy rather than using voice or text independently. The final ensembled model will be integrated with the Medora system to provide real-time risk level prediction to help operators assess and triage calls and take appropriate action.