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| --- | --- | --- | --- | --- | --- |
| **Proposal Title:** | Augmented Machine Intelligence for Critical Infrastructure | | | | |
| **Principal Investigator:** | Shiloh Elliott | | **Directorate:** | N&HS | |
| **INL Co-investigator:** | Ashley Shields | | **Directorate:** | EES&T | |
| **INL Co-investigator:** | Ross Kunz | | **Directorate:** | EES&T | |
| **Initiative:** | 5.2 Resilient Critical Infrastructures | | | | |
|  | | | | | |
| **Budget Summary** | | **Funding Recipient** | | | **Budget ($)** |
| Fiscal Year 23 | | Idaho National Laboratory | | | 350,000 |
| Fiscal Year 24 | | Idaho National Laboratory | | | 350,000 |
| Fiscal Year 25 | | Idaho National Laboratory | | | 300,000 |
| **Total:** | | | | | 1,000,000 |

ABSTRACT

Critical infrastructure analysis is key to United States (US) energy, water, transportation, and health care resilient operations under unknown and changing operational conditions creating uncertainty. Current machine learning approaches are statistical, highly specialized, and rely on well-defined problem sets for a narrow application space. These approaches are brittle and often fail in national security space due to challenges of critical-safety performance in unknown operational conditions. One technical challenge is the simultaneous characterization and contextualization of critical infrastructure entities, operations, and systems. The current human-based decision-making process is manual, uses sparse and disparate data sets, and requires causal inference for reasoning to reduce decision uncertainty. The current approach is error-prone, brittle, quickly becomes obsolete, and does not scale and adapt to address emerging national security problems [1]. Recent data science approaches address these limitations by developing methods inspired by human analytical capabilities. These approaches utilize reasoning, multidisciplinary ensemble, and fusion methods [1]–[4]. We propose a novel ensemble modeling approach that will implement data fusion techniques, diverse data sets, and machine learning methods to build a data fusion framework capable of accurate decision-making and can adapt to unknown operational conditions. The framework will go beyond standard, content-only machine learning by providing an analytical framework capable of characterizing and contextualizing critical infrastructure entities, operations, and systems. Success would result in a first-in-domain method with decision-making on par with human-based critical infrastructure characterization and contextualization along with reasoning capabilities that will be able to scale with emerging national security needs.

# SIGNIFICANCE

Engineering decision intelligence with respect to critical infrastructure entities and their systems is a nuanced manual process involving the analysis of numerous disparate data sets and the integration of multiple stakeholder insights across a diverse set of government and private institutions. Decision intelligence surrounding critical infrastructure entities plays an important role in understanding how an entity (e.g., a power station) operates within its environment. This information can be used to gain insights into 1) the infrastructure sector housing the entity, 2) hidden vulnerabilities, 3) entity importance to surrounding populations, and 4) cross-sector dependencies (e.g., transportation to supply a water plant with chlorine). This understanding is vital to maintaining and increasing the nation’s critical infrastructure resilience posture. The United Nation’s recent ‘Climate Change 2022: Mitigation of Climate Change’ report stresses the importance of infrastructure when addressing the impending threats of climate change [5]. Addressing the climate challenge will require the creation of new infrastructure and retrofitting of old infrastructure. These activities have the potential to increase the nation’s infrastructure resilience posture or introduce unknown vulnerabilities. Actions taken by Russia during the invasion in Ukraine also demonstrate in importance of civilian and military infrastructure, both of which were primary targets during initial phase of the invasion [6]. The method described in this proposal would enable the timely characterization of critical infrastructure entities and sound decision-making based on data-driven insights increasing resilience and harden infrastructure systems against potential foreign aggression.

Allowing for the responsible updating and creation of infrastructure to maintain or increase resiliency would also allow for the hardening of infrastructure systems against foreign aggression. Current approaches require significant resources, man-hours, and produce knowledge that can be difficult to update and can miss vital data components, and do not scale with anticipated challenges in the national security and intelligence application spaces. Machine learning techniques have undergone many technological advances; however, standard machine learning technologies are still primarily focused on statistical learning (e.g., content only). These conclusions lack context and do not generalize to applications outside of a narrow focus [7].

This proposal seeks to develop and quantify performance of a first-in-domain multimodal data fusion method for critical infrastructure decision intelligence. Data fusion approaches have been in use for sensor research since the 1970s, but with recent advances in multimodal data and machine learning, data fusion approaches can now be expanded to multiple domains [8]. For the purposes of this proposal, we are using the original definition of data fusion “A multi-level process dealing with the association, correlation, combination of data and information from single and multiple sources to achieve refined position, identify estimates and complete and timely assessments of situations, threats and their significance.” [9] We will also be utilizing the abstraction level data fusion approach, which will allow for the study of early, late, and hybrid fusion techniques [10]–[12]. This will allow for the careful tuning and testing of the methodology. Our intention is to combine multiple models and their outputs into a novel fusion framework capable of contextualizing critical infrastructure entities. A multimodal data fusion approach of this type has the potential to transcend the barriers between second wave artificial intelligence (AI) (statical leading) and third wave AI models that will have the ability to contextualize the reasoning behind their conclusion [13].

Three distinct advantages over the current limits of practice evolve by successfully creating the proposed novel fusion modeling approach using multimodal data sets and machine learning methods to build a data fusion framework capable of accurate decision-making under uncertainty that can adapt to unknown operational conditions. First, the team will develop a first-in-domain data fusion methodology with performance on par with or exceeding human-based critical infrastructure characterization and contextualization analytic and reasoning capabilities leapfrogging current manual critical infrastructure analysis methods. Second, the approach addresses future national security concerns of limited workforce, increased deception, increased events, and the need for responsive, agile, and faster field response by developing a trustworthy, augmented intelligence method that can mimic human reasoning capability. A noted national priority [1], [14], [15]. Third, the method can be readily adapted, or generalizable, to unknown operational conditions. Performance will be measured on multiple levels. Individual model performance will be determined using the domain recommended method for accuracy and performance [16] . Metrics for overall fusion framework accuracy will be determined after abstraction level has been established. Overall computation complexity will be kept at a minimum to allow for a dynamic modeling process.

# RESEARCH PLAN

The project’s research plan will take place in two stages with each taking 18 months. The first stage will establish data streams and initial models to be used in the fusion process. The project will prioritize existing data streams reducing the time spent on data collection and ensure framework applicability beyond a laboratory environment. Models will build upon standard machine learning and statistical models [17]. These models have large bodies work associated with them and are well vetted in multiple domains. Models will be augmented using hyperparameter tuning and early data fusion experimentation in line with the project’s goal. Early data fusion practices will build upon current limit of practice techniques utilized in work with analogous research questions [18]–[20]. The team will have to establish data pipelines and cleaning process for the diverse set of data streams that will be needed for project success. This will require a review of recommended data pipeline practices, a well-documented process used frequently in the private, non-government organization, academic, and government space [21]–[24].

Models for this stage will fall into four modeling families.

***Classification***, the identification of critical infrastructure, will draw from past modeling work conducted by the research team and additional related work [25], [26]. Accuracy and fitting metrics (loss characterizations) are used to measure classification model performance of this type [27]. Given the research team’s experience with remote sensing and object detection, the team will plan to utilize DenseNet161 and the Local Interpretable Model-Agnostic Explanations framework during initial classification efforts [28], [29]. However, prior to algorithm selection, the team must characterize the data; for example, the team seeks to address challenges like under specification to optimize real-world performance[30].

***Spatial analysis*** is key to crucial critical infrastructure components, single-point failures, and process flow knowledge. Given the diversity of spatial analysis, exact modeling approaches will be established in parallel with data pipeline efforts. We predict that models in this family will follow geospatial data fusion methods [31], [32]. Specially the Step-wise Weighted Assessment Ratio Analysis (SWARA) method. SWARA will allow the project to weight the outputs of different spatial models when drawing conclusions. For example, using the aspect ratio conclusion from a digital elevation model in conjunction with a shortest path routing algorithm when establishing a potential critical infrastructure system laydown.

***Attribute characterization*** will use currently available data collected during the All-Hazards Analysis (AHA) data build out effort, a unique Idaho National Laboratory (INL) resource. Combining the data collected in AHA with regression techniques will enable the identification of previously unknown attributes of systems and facilities within a critical infrastructure entity. For attribute characterization, we will utilize a stacking generalization ensemble technique which will allow for the combined use of several regression-based models. Cross-validation is integrated into stacking generalization and will serve as the model accuracy metric [33].

Finally, ***natural language processing (NLP****)* for analysis and discovery of critical infrastructure systems information contained within numerous open-source documents that detail the operations of critical infrastructure systems. NLP solutions will focus on building on leading-edge developments in establishing meaning, context, and causality in NLP analysis [4], [34]–[36]. If successful we intend to use causality analysis to assist in the identification of operational and dependency identification for critical infrastructure systems. Validation of causal analysis can be challenging, and an ensemble method will be employed to determine accuracy. With this approach, we will associate agreement between models as an indication of performance [35]. For initial analysis the team will leverage Bidirectional Encoder Representations from Transformers for Natural Language Understanding (NLU) and the model’s derivative InferBERT. Given the bidirectional nature of both models they will be ideal in identifying critical infrastructure systems and potential dependencies and inter- dependencies [37], [38]. The team will leverage the reference data catalog associated with AHA for initial training material NLP implementation. The reference catalog records which documents were used in establishing a critical infrastructure node or dependency. Given the complexity of this proposed task, the team will establish in stage one a single critical infrastructure sector to focus modeling efforts on. When successful, a similar blueprint can be applied to additional sectors.

The second stage of the project will involve experimentation with late-stage and hybrid data fusion. Late-stage fusion takes place at the decision level after initial modeling has been completed. Late-stage fusion approaches vary and are dependent on modality combinations and research goals [39]. Exact late-stage fusion approaches will be determined after initial modeling results have been compiled. The team intends to use late fusion as a final step in the creation of the critical infrastructure entities. Hybrid fusion results are a combination of both early and late data fusion methods where data fusion techniques are applied to feature level products that will continue to be processed [8], [10], [18]. Accuracy during stage two will be monitored using the metrics established during stage one. A final measure of accuracy will be verification and validation via the comparison of the fusion frame data entity to one developed by a human analyst.

Deliverables for each stage and year are listed below in Figure 1. Figure 2 notes a timeline for the project’s stages. Budgets for each year would require a funding level of $350k for years one and two and $300k for year three. The final project deliverable would take the form of a data fusion framework comprised of the components described above. This deliverable would ideally be capable of characterizing and contextualizing a critical infrastructure system in a defined geographic area.

# PRODUCTS AND DELIVERABLES

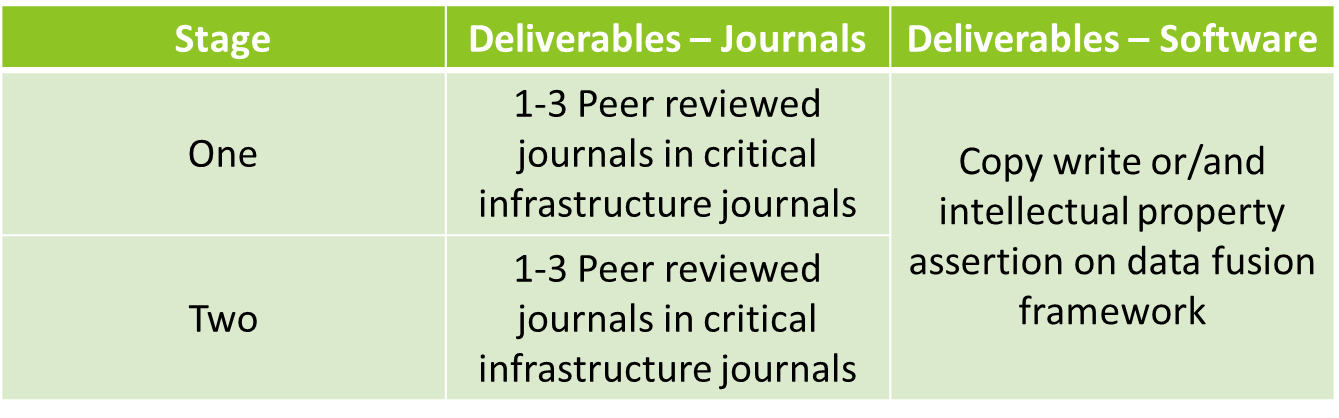


Figure 1. Listed deliverables for each stage of the proposed project.

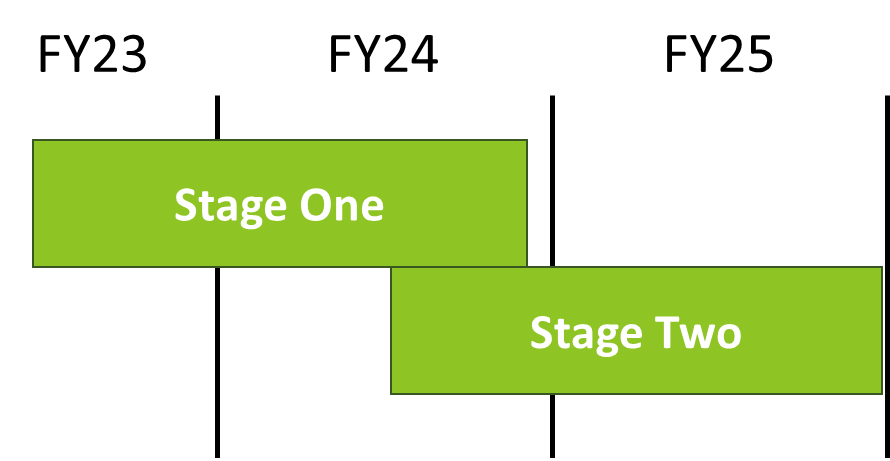


Figure 2. High-level timeline for each stage over the three-year potential project.

# POTENTIAL HARVEST STRATEGY

If successful, this research will produce several new capabilities at the first and second stages of the project. Stand-alone and ensemble methods established in stage one will advance knowledge through the publication of peer-reviewed journal articles and conference presentations. The final framework developed in stage two will support developing a differentiating, next generation AI capability in the National and Homeland Security space. A successful fusion framework could also be of great value to the Department of Homeland Security (DHS) by greatly enhancing a DHS analyst’s ability to perform their work quickly and efficiently, but also allowing DHS to utilize their large data silos, the products of multiple years of work, to more effectively respond to national security threats. INL would benefit from the roadmap this project leaves behind for data fusion framework creation and integration at completion. The roadmap could be applied to other national and homeland security domains areas like cybersecurity or nuclear non-proliferation. Additionally, a successful fusion framework could enable future next generation AI research. For example, Pacific Northwest National Laboratory’s Mega AI initiative. Energy Efficiency and Renewable Energy’s Waterpower Technology Office, National Nuclear Security Administration (NNSA) NA-22’s data science portfolio, and most notably NNSA NA-24’s Concepts and Approaches subprogram has shown a willingness to fund critical infrastructure work enabled by advanced analytics and machine learning for nuclear fuel cycle applications. This funding potential could also extend to the next gen AI methodology resulting from this work. At maturity the framework could be utilized by the DHS and the Cybersecurity and Infrastructure Security Agency in their national security efforts.

# RESEARCH TEAM CURRICULUM VITAE

Team curriculum vitae are located under ‘Attachments’ in Laboratory Overhead Investment Electronic Submission System). File names are listed below.

* Shiloh Elliott – Elliott\_CV.pdf
* Ashley Shields – Shields\_CV.docx
* Ross Kunz – kunz\_CV.pdf

# BUDGET

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **A: Research Tasks** | **FY-23 ($k)** | **FY-24 ($k)** | **FY-25 ($k)** | **Total ($k)** |
| Classification |  |  |  |  |
| * Data Preparation & Processing | 5 | 5 |  | 10 |
| * Modeling | 25 | 15 | 10 | 50 |
|  |  |  | Sub-Total | **60** |
| Attribute characterization |  |  |  |  |
| * Data Preparation & Processing | 10 | 10 | 5 | 25 |
| * Modeling | 40 | 40 | 15 | 95 |
|  |  |  | Sub-Total | **120** |
| Spatial Analysis |  |  |  |  |
| * Data Preparation & Processing | 15 | 5 |  | 20 |
| * Modeling | 40 | 40 | 15 | 95 |
|  |  |  | Sub-Total | **115** |
| Natural Language Processing |  |  |  |  |
| * Data Preparation & Processing | 50 | 5 | 5 | 60 |
| * Modeling | 90 | 50 | 20 | 160 |
|  |  |  | Sub-Total | **220** |
| Early Fusion | 40 | 10 |  | 50 |
| Late Fusion |  | 30 | 70 | 100 |
| Hybrid Fusion | 25 | 70 | 60 | 155 |
| Publications/Conference | 10 | 50 | 50 | 110 |
| Framework Creation |  | 20 | 50 | 70 |
| **Total task budget** | **350** | **350** | **300** | **1000** |
|  |  |  |  |  |
| **B: INL Researchers** | **FY-23 ($k)** | **FY-24 ($k)** | **FY-25 ($k)** | **Total ($k)** |
| Shiloh Elliott | 117 | 117 | 110 |  |
| Roz Kunz | 80 | 80 | 74 |  |
| Ashley Shields | 128 | 128 | 110 |  |
| Hold for additional INL SME (infrastructure) Ex. Ryan Hruska | 12 | 12 | 0 |  |
| Hold for additional INL SME (modeling) Ex. Katya Le Blanc | 7.5 | 7.5 | 0 |  |
| **Total INL labor** | **345** | **345** | **294** | **984** |
|  |  |  |  |  |
| **C: Nonlabor** | **FY-23 ($k)** | **FY-24 ($k)** | **FY-25 ($k)** | **Total ($k)** |
| Conference | 5 | 5 | 6 | **16** |
| **Total nonlabor** | 5 | 5 | 6 | **16** |
|  |  |  |  |  |
| **B+C: Total Budget Request** | **350** | **350** | **300** | **1000** |

# DATA MANAGEMENT PLAN

Much of the data needed for this proposed project already exists. The team will rack and stack existing data sets in the initial steps of the project. When necessary, the team will utilize SQLite for database needs. In instances with unstructured data a MongoDB will be utilized. All data will be subject to exploratory data analysis upon initial data pull. This will record important metadata for later publication and eliminate outliers and account for normalization when necessary. All code and associated data will be stored on HPC GitLab. Modeling will take place on a Lambda Quad Workstation (already in operation). Modeling results and test bed activities will be recorded by embedded listeners in all modeling code. This will preserve raw model performance for later collation for conference attendance and journal publication.

## Data Types and Sources

The following describes the data to be used for this research and the proposed deliverables.

* Regulatory documents and databases maintained by state and federal government entities. This is not an inclusive list. These data sets have potential use in a number of modeling efforts.
  + US Environmental Protection Agency – Safe Drinking Water Information System
  + US Energy Information Administration – Energy data bases. Free
  + US Geological Survey - National Hydrography Dataset. Free
  + US Department of Transportation - National Pipeline Mapping System – Use permission is required and has been granted
* Below are data sets that will be used for specific modeling efforts.
  + Classification
    - National Agriculture Imagery Program – imagery data in the visible spectrum. Free.
    - WorldView – imagery data in the visible spectrum. Free through the National Geospatial-Intelligence Agency.
  + Attribute Characterization
    - AHA’s taxonomy and database – Taxonomy to be used to establish characterization existing database to be used as training data for characterization. Free.
  + Spatial Analysis
    - USGS’s National Digital Elevation Model. Free
    - State level infrastructure data. Need to be identified.
  + Natural Language Processing
    - AHA’s document database – citation document associate with graph creation. Free.
    - Federal and state regulatory documents – These documents are published on regular basis and follow a similar pattern in sentence structure.

## Data Sharing and Data Preservation

Unclassified and non-proprietary final data shall be made available for a period of at least five years after the project ends. This data will be stored at INL as a digital research record and even after the public availability period, may be requested and retrieved from INL’s records repository. Also,

* Publishers of research publications may store and make the final data available in addition to INL.
* A third-party may request to preserve this data after the five-year term at INL. The request will be evaluated by the project team and the INL Research Library.
* All data resulting from this project are available to the government upon request through the government use license in place at INL.
* All Scientific and Technical Information (STI) products, including software and data, shall go through STI review using INL’s Lab Review System (LRS) before it is released for publication or disseminated outside of INL in any format or medium.
* Learn more about STI and the LRS process and contacts at the [LRS website](https://lrshelp.inl.gov/SitePages/LRSHome.aspx).
* Direct routine and iterative sharing of information with an entity contractually involved with the work—and only with such entity—does not require formal review through the LRS process. However, the recipient must be informed that the information has not been approved for unrestricted release, and the originator is solely responsible for obtaining and documenting any necessary reviews, particularly for classification.

Final data from this project may have immediate impact both within the research field and more broadly to society. Therefore, INL will make available the data necessary to validate research findings in the project publications. The Department of Energy’s Office of Scientific and Technical Information (OSTI) shall be notified of all publications resulting from this project. The final scientific and technical data used to generate charts, graphs, and tables in the all publications resulting from this project will be preserved in Microsoft Excel or a text-based comma delimited file.

## Data Protection

Data may be withheld from publication when appropriate and necessary to protect confidentiality, personal privacy, personally identifiable information, and US national, homeland, and economic security; recognize proprietary interests, business confidential information, and intellectual property rights; and avoid significant negative impact on innovation and US competitiveness. The principal investigator for this project shall determine if there is data requiring this protection.

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