**C.1 Publications**

**Are there publications or manuscripts accepted for publication in a journal or other publication (e.g., book, onetime**

**publication and monograph) during the reporting period resulting directly from this award?** Yes

|  |
| --- |
| 1/ Ramon Maldonado, Travis R. Goodwin, and Sanda M. Harabagiu, “Memory-Augmented Active Deep Learning for Identifying Relations Between Distant Medical Concepts in Electroencephalography Reports”, in *Proceedings of the American Medical Informatics Association Informatics Summit*, pp 156-165, San Francisco, CA, USA, March 2018 (**The AMIA Clinical Research Informatics Award**)2/ Travis R. Goodwin, Michael A. Skinner and Sanda M. Harabagiu, “Automatically Linking Registered Clinical Trials to their Published Results with Deep Highway Networks”, in *Proceedings of the American Medical Informatics Association Informatics Summit*, pp 54-63, San Francisco, CA, USA, March 2018 3/ Travis R. Goodwin and Sanda M. Harabagiu, “Inferring Clinical Correlations from EEG Reports with Deep Neural Learning”, in *Proceedings of the American Medical Informatics Association Annual Symposium (AMIA)*, pp 770-779, Washington, DC, USA, November 2017 (**Homer Warner Award**)4/ Ramon Maldonado, Travis R. Goodwin, Michael A. Skinner and Sanda M. Harabagiu, “Deep Learning Meets Biomedical Ontologies: Knowledge Embeddings for Epilepsy”, in *Proceedings of the American Medical Informatics Association Annual Symposium (AMIA)*, pp 1226-1235, Washington, DC, USA, November 2017 5/ Stuart Taylor, Travis R. Goodwin and Sanda M. Harabagiu, “An Evaluation of Syntactic Dependency Parsers on Clinical Data”, *the American Medical Informatics Association Annual Symposium (AMIA)*, submitted, March 20176/ Ramon Maldonado, Travis R. Goodwin and Sanda M. Harabagiu, “Active Deep Learning-Based Annotation of Electroencephalography Reports for Cohort Identification”, in *Proceedings of the American Medical Informatics Association Joint Summits on Clinical Research Informatics (AMIA-CRI)*, pp 229-238, San Francisco, CA, USA, March 2017 (**Nominated for** **Distinguished Paper Award**)7/ Travis R. Goodwin, Ramon M. Maldonado and Sanda M. Harabagiu (2017) “Automatic Recognition of Symptom Severity from Psychiatric Evaluation Reports”, *Journal of Biomedical Informatics*, 75 S71-S84 8/ Travis R. Goodwin and Sanda M. Harabagiu (2017) “Knowledge Representations and Inference Techniques for Medical Question Answering”, *ACM Transactions on Intelligent Systems and Technology*, Volume 9, Issue 2, October 2017. 9/ Travis R. Goodwin and Sanda M. Harabagiu, (2018) “Learning Relevance Models for Patient Cohort Retrieval”, *Journal of the American Medical Informatics Association (JAMIA) Open*, Indiana, accepted for publication. |
|  |

**C.2 Website(s) or other Internet site(s)**

"Nothing to Report".

**C.3 Technologies or techniques**

The UTD team has designed a novel deep learning method for Identifying relations between distant medical concepts in Electroencephalography Reports, which received the *AMIA Clinical Research Informatics Award* at the 2018 AMIA Informatics Summit. The automatic identification of relations between medical concepts in a large corpus of Electroencephalography (EEG) reports is an important step in the development of an EEG-specific patient cohort retrieval system as well as in the acquisition of EEG-specific knowledge from this corpus. EEG-specific relations involve medical concepts that are not typically mentioned in the same sentence or even the same section of a report, thus requiring extraction techniques that can handle such long-distance dependencies. To address this challenge, we developed a novel framework which combines the advantages of a deep learning framework employing Dynamic Relational Memory (DRM) with active learning.

The team led by Prof. Harabagiu has also developed a novel method for inferring the clinical correlations from EEG Reports with Deep Neural Learning. The paper describing this method has received the Homer Warner Award at the 2017 AMIA Symposium. The role of the clinical correlation section is not only to describe the relationships between findings in the EEG report and the patient’s clinical picture, but to also explain and justify the relationships so as to convince any interested health care professionals. Consequently, the clinical correlation section of an EEG report is expressed through natural language, meaning that the clinical correlations documented in the clinical correlation section are qualified and contextualized through all the subtlety and nuance enabled by natural language expression. For this reason, while it might appear sufficient to simply extract individual findings or medical concepts from the clinical correlation section, describing and justifying the clinical correlations requires producing coherent natural language. This requirement makes inferring the expected clinical correlation section from an EEG report a challenging problem because it requires not only identifying the correct clinical correlations, but also expressing those correlations through natural language which is by the content of the EEG report as well as the neurologist’s medical knowledge and accumulated experience.

In this project, the UTD team has developed a novel Deep Section Recovery Model (DSRM) which applies deep neural learning on a large body of EEG reports in order to infer the expected clinical correlations for a patient based solely on the natural language content in his or her EEG report. When using standard evaluation metrics for natural language generation, the DSRM model outperformed current state-of-the-art methods, implemented using sequence-to-sequence techniques. Furthermore, when analyzing the automatically inferred clinical correlation sections produced by the DSRM, we manually reviewed 100 randomly selected EEG reports from the test set by comparing the inferred clinical correlation sections to the gold-standard clinical correlation sections written by the neurologists. The over-all quality of the inferred clinical correlation sections was assessed using the Likert scale, the DSRM method results obtaining an average score 3*.*491, indicating that the inferred clinical correlation sections are generally accurate, but may contain minor additional erroneous information or have minor omissions.

Finally, the UTD team has also developed a novel learning-to-rank framework for patient cohort retrieval. Ranking of the patients in the cohort was essential in the usability studies performed with the MERCuRY system, as it enabled neurologist researchers to rapidly identify effective interventions for epilepsy accompanied by mental health comorbidities. However, not all the patients from the cohorts discovered by MERCuRY were relevant to the cohort criteria. Relevance judgements produced by neurologists indicated limitations of the system, but also provided important lessons that can be used for learning how to rank patients. Inspired by this observation, we designed a *learning patient cohort retrieval* (L-PCR) system using the publicly-available collection of electroencephalography (EEG) reports from the Temple University Hospital (TUH) EEG Corpus. Patient cohorts were recognized from the TUH EEG Corpus based on descriptions provided by practicing neurologists. Specifically, we trained and evaluated the L-PCR system using 30 cohort descriptions generated by four practicing neurologists.

Unlike traditional patient cohort retrieval systems, such as MERCuRY, the L-PCR system uses a *learning-to-rank* approach for identifying patient cohorts that takes advantage of physician feedback. The learning-to-rank paradigm allows the L-PCR system to consider *relevance judgments* performed by clinicians to *learn* an improved patient relevance model used for retrieving and ranking patients for any given cohort descriptions.

Our patient cohort retrieval system which incorporates machine learning operating on features encoding thousands of different strategies for representing queries, EHRs, and their interactions with the goal of learning how to rank patient cohorts based on clinicians’ feedback (the L-PCR system) surpassed previously published state-of-the-art NDCG score by 27.1%.

**C.4 Inventions, patent applications, and/or licenses**

**Have inventions, patent applications and/or licenses resulted from the award during this reporting period?** Yes No

**If yes, has this information been previously provided to the PHS or to the official responsible for patent matters at the grantee**

**organization?** Yes No

**C.5 Other products and resource sharing**

**C.5.a Other Products**

**Nothing to Report**

**or Upload other products and resources**

**C.5.b Resource sharing**