## Innovative techniques to construct powerful artificial intelligence algorithms for st-elevation myocardial infarction

S. Mehta<sup>1</sup>, S. Niklitschek<sup>2</sup>, F. Fernandez<sup>2</sup>, C. Villagran<sup>2</sup>, J. Avila<sup>2</sup>, G. Cardenas<sup>2</sup>, R. Rocuant<sup>2</sup>, F. Vera<sup>2</sup>, A. Frauenfelder<sup>1</sup>, D. Vieira<sup>1</sup>, S. Quintero<sup>1</sup>, G. Pinto<sup>1</sup>, Y. Vijayan<sup>1</sup>, S. Merchant<sup>1</sup>, D. Bou Daher<sup>1</sup>

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**Background:** With the sudden advent of Artificial Intelligence (AI), incorporation of these technologies into key aspects of our working environment has become an ever so delicate task, especially so when dealing with timesensitive and potentially lethal scenarios such as ST-Elevation Myocardial Infarction (STEMI) management. By further expanding into our successful experiences with Al-guided algorithms for STEMI detection, we implemented an innovative ensemble method into our methodology as we seek to improve the algorithm's predictive capabilities.

**Purpose:** Through the ensemble method, we combined two ML techniques to boost our previous experiments' accuracy and reliability.

**Methods:** Database: EKG records obtained from Latin America Telemedicine Infarct Network (Mexico, Colombia, Argentina, and Brazil) from April 2014 to December 2019. Dataset: Two separate datasets were used to train and test two sets of Al algorithms. The first comprised of 11,567 records and the second 7,286 records, each composed of 12-lead EKG records of 10-second length with sampling frequency of 500 Hz, including the following balanced classes: unconfirmed & angiographically confirmed STEMI (first model); angiographically confirmed STEMI only (second model); and, for both models, we included branch blocks, non-specific ST-T abnormalities, normal, and abnormal (200+ CPT codes, excluding the ones included in other classes). Label per record was manually checked by cardiologists to ensure precision (Ground truth). Pre-

processing: First and last 250 samples were discarded to avoid a standardization pulse. An order 5 digital low pass filter with a 35 Hz cut-off was applied. For each record, the mean was subtracted to each individual lead. Classification: The determined classes were STEMI and Not-STEMI (A combination of randomly sampled normal, branch blocks, non-specific STT abnormalities and abnormal records – 25% of each subclass). Training & Testing: The last dense layer outputs a probability for each record of being STEMI or Not-STEMI. These probabilities were calculated for each model (Model 1 trained with Complete STEMI dataset and Model 2 trained with confirmed STEMI only dataset) and aggregated using the mean aggregation to generate the final label for each record. A 1-D Convolutional Neural Network was trained and tested with a dataset proportion of 90%/10%; respectively. Results are reported for both testing datasets (Complete and confirmed STEMI only records).

**Results:** Complete STEMI Dataset: Accuracy: 96.5% Sensitivity: 96.2% Specificity: 96.9% – Confirmed STEMI only Dataset: Accuracy: 98.5% Sensitivity: 98.3% Specificity: 98.6%'

Conclusion(s): While Model 1 and Model 2 achieved similar performances with promising results on their own, applying a combination of both through the ensemble model exhibits a clear improvement in performance when applied to both datasets. This provides a blueprint for advanced automated STEMI detection through wearable devices.

