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Artificial Neural Networks Can Predict Trauma Volume and Acuity Regardless of Center Size and Geography: a multicenter study

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Abstract

Background—Trauma has long been considered unpredictable. Artificial neural networks (ANN) have recently shown the ability to predict admission volume, acuity and operative needs at a single trauma center with very high reliability. This model has not been tested in a multicenter model with differing climate and geography. We hypothesize that an artificial neural network can accurately predict trauma admission volume, penetrating trauma admissions, and mean ISS with a high degree of reliability across multiple trauma centers.

Methods—Three years of admission data was collected from five geographically distinct US level 1 trauma centers. Patients with incomplete data, pediatric patients and primary thermal injuries were excluded. Daily number of traumas, number of penetrating cases, and mean ISS was tabulated from each center along with National Oceanic and Atmospheric Administration data from local airports. We trained a single two-layer feed-forward ANN on a random majority (70%) partitioning of data from all centers using Bayesian Regularization and minimizing mean squared error. Pearson's product-moment correlation coefficient was calculated for each partition, each trauma center, and for high and low volume days (>1 standard deviation above or below mean total number of traumas).

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Author Contributions:
BMD, DPS and ODG were involved in study design and analysis and interpretation. All authors were actively involved in data acquisition as well as drafting and critical revision of the manuscript.

Results—5,410 days were included. 43,380 traumas, including 4,982 penetrating traumas. The mean ISS was 11.78 (SD=6.12). On the training partition, we achieved R = 0.8733. On the testing partition (new data to the model), we achieved R = 0.8732, with a combined R = 0.8732. For high and low volume days, we achieved R = 0.8934 and R = 0.7963, respectively.

Conclusions—An ANN successfully predicted trauma volumes and acuity across multiple trauma centers with very high levels of reliability. The correlation was highest during periods of peak volume. This can potentially provide a framework for determining resource allocation at both the trauma system level and the individual hospital level.

Level of Evidence—Level III, prognostic

Background

Physicians and nurses with extensive experience in emergency departments or trauma centers often report a somewhat predictable variation to the ebb and flow of trauma admissions. This has given rise to the belief, at some centers, that there is a “trauma season.” This ebb and flow can have significant effects on the workflow of trauma centers. The ability to forecast these variations in trauma admissions at a granular level, particularly with regards to times of increased patient volume, has the potential to allow hospitals to adjust staffing and resource allocation to allow for optimal patient care. Unfortunately, quantifying this ebb and flow has been elusive.

In recent years, an increased focus has been placed on building and implementing tools to predict illness severity, complications, outcomes, and the cost associated with treatment within medicine and surgery.(1–5) Classically, this has been done with conventional statistics or scoring systems. However, machine-learning technology has been useful across various medical specialties, including predicting outcomes in traumatic brain injuries, post-surgical outcomes and lengths of stay in trauma and other surgical subspecialties. (6–11) Recently, there have been two major uses in characterizing skin tumors malignancy (12), and identifying pneumonia-like structures on chest x-ray. (13) One class of machine-learning algorithms, known as an Artificial Neural Networks (ANNs), has been used in some of these models to predict an outcome based on pattern recognition.(1, 4, 5) These tools often prove useful as they are able to improve their predictive ability, or “learn”, as they encounter new data, and they benefit from internal validation and testing.(1, 2, 5, 6, 14, 15) These ANNs are computational constructs that can segregate inputs and pattern recognize within these data to make predictions, using historical outputs. Over time, they can be trained to continue to fine tune their predictions as more input and output data is provided, and overtime can “learn” to make better predictions, in a way that, for example, logistic regression and most conventional statistics cannot. One challenge this may present is that they may require larger computational infrastructure to facilitate the increased computational demands and to provide real time data input and learning.(1, 4, 5)

Previous studies have attempted to identify patterns in trauma volume based on temporal and weather-related variations.(16–31) Using retrospective data, temporal and weather-related trends have been identified. Nights and weekends have been associated with higher admission rates, injury severity and need for emergent operation.(20, 29) Seasonal patterns have also been identified with summer months having higher rates of admissions.(16, 18, 22) Studies attempting to identify patterns in trauma admission and severity based on specific weather patterns, such as rain or sunshine have been more mixed.(16–18, 22, 26) Emergency department visits, ED radiology usage, burn admissions and orthopedic volumes have also identified some temporal and weather-related trends. (19, 23, 25, 27, 28) Each of these studies was unable to integrate these past trends in weather, season, and time and create a predictive model for trauma volume and acuity. In an earlier study, we demonstrated that an ANN, using historical admission volumes and weather data, could be used to predict trauma volume, acuity and operative volume with a high degree of accuracy at a single trauma center.(31, 32) Variability in weather, trauma center volume and geography limited this initial study. A multi-center study was needed to determine if this tool had applicability to the broader trauma environment.

The goal of this study was to integrate trauma admission and weather data from several trauma centers that are distinct geographically, climatologically, and in terms of trauma volume and acuity. We then sought to use this data to create and train a multicenter artificial neural network to predict trauma admissions at an individual center. We hypothesize that the ANN will predict trauma admission volume and severity of injury with a high degree of reliability within multiple, varied trauma centers.

Methods

Three years (July 1, 2013 to June 30, 2016) of trauma admission data was collected from five geographically and climatologically distinct US trauma centers (Nashville, TN, Denver, CO, Houston, TX, Des Moines, IA, Rochester, NY). Pediatric patients and primary thermal injuries were excluded. At each center, the daily number of traumas, number of penetrating cases, and mean ISS was tabulated for each day of the study across the five centers. For days in which 0 traumas were recorded at a center, the mean ISS was not computable and therefore not included in training. These data are described graphically using LOWESS for fitting across the year following normalization by the median for each trauma center, as well as with heat maps showing both relative and absolute frequency of trauma volume per hour and descriptive statistics. Heat maps required data for time of arrival and date of arrival only. Data was also extracted from the National Oceanic and Atmospheric Administration's (NOAA) Climate Online Database to capture weather readings from one of each center's local airport (Nashville International Airport, Denver International Airport, George Bush Intercontinental Airport, Des Moines International Airport, Greater Rochester International Airport).(33)

We trained a single two-layer feed-forward Artificial Neural Network (ANN) with 15 sigmoid hidden neurons and 3 linear output neurons on a random majority (70%) partitioning of the data from all centers using Bayesian Regularization and minimizing mean square error over all targets. One hidden layer was chosen to prevent overfitting this model with only 7 likely collinear inputs and 3 outputs, we chose 15 nodes as it minimized the mean squared error (MSE) while providing similar fit on the test and training partition. As input to this model we take the date parsed into the 1) day of the year, 2) the day of the week, 3) the daily high temperature (°F), 4) the daily low temperature (°F), 5) precipitation (binary) 6) snow (binary), and 7) center identifier (Figure 1). High and low temperature were both incorporated despite co-linearity, which the ANN can account for during weight assignment. This data predicted: 1) number of trauma contacts that will present on a given date, 2) the number of penetrating trauma contacts, and 3) and the mean ISS score for that day. Fifteen percent of data (of the total trauma days) were reserved each for testing and validation, and Pearson's product-moment correlation coefficient was calculated for the output versus target spaces on each of the partitions: training, testing and validation. Mathematical, statistical and graphical analysis was performed with offline MATLAB R2017b.

Results

Our parameter of investigation in this study is the 24-hour calendar day, to which we assign measures of trauma volume and acuity. Across the five study centers and three study years there were 5,480 potential days of study, of which 5,410 days were included with 70 being excluded due to insufficient data. This captured 43,380 traumas, including 4,982 penetrating traumas. These data are summarized by center in Table 1.

We analyzed temporal patterns across the five centers using heat maps and curves capturing the seasonal change in trauma volume. Figure 2 shows the relative frequency of all traumas per hour for all centers combined. Figure 3 shows the relative frequency of traumas per hour (color bar, right), normalized for each center's mean number of traumas (color bar = 1) for each center. These data reveal similar temporal patterns across the week between these centers, with few trauma contacts in the morning at all centers, particularly on weekdays, and a higher density of trauma contacts over nights and weekends. At all centers, the weekend nadir in trauma contacts is later than on weekdays. Figure 4 captures these same data, but represents the absolute frequency of trauma per hour, where the color bars are consistent across all centers (using Houston's trauma as the metric due to the largest volume).

Fitting of relative trauma volume versus day of year showed, at all centers individually and when combined, seasonal variation of overall trauma volume (Figure 5). At all centers, mid-year (summer) had above-median trauma volume, while mid-winter demonstrated the smallest volume. This pattern held when all centers data was combined (dashed blue line). While the overall pattern (summer has higher volume than winter) held for each center, there were more subtle differences between centers in when the precise peaks and nadirs occur, and how long these peaks and trough lasts.

We successfully trained an ANN with the seven input variables to predict the number of daily traumas, the number of penetrating cases, and the mean daily ISS. On the partition dedicated to model training, we achieved $R = 0.8733$, on the testing partition (new data to the model) the model achieved $R = 0.8732$, with a combined dataset $R = 0.8732$.

The correlation coefficients were also calculated for each location on the combined dataset: Nashville $R = 0.8729$, Des Moines $R = 0.7481$, Rochester $R = 0.9093$, Houston $R = 0.8895$, Denver $R = 0.7721$. We also identified high volume trauma days (days greater than one standard deviation above average for total number of traumas at that specific center) and compute the correlation coefficient for all three output as R = 0.8934. Similarity, we identified low volume days and, on these days, found R = 0.7963. This indicates the model has better performance on high volume trauma days than low volume trauma days.

Discussion

We have analyzed the trauma landscape at multiple level one trauma centers of varying size, climate and geographic location in order to determine if an ANN can reliably predict trauma admission volume, penetrating trauma volume, and mean ISS. Our correlation coefficients demonstrate success with this methodology. There is a dearth of published literature on this application of ANNs to predict trauma volume and acuity. We have previously demonstrated the predictive ability of ANNs with respect to trauma admissions, acuity, and need for urgent operation at a single level 1 trauma center.(32) This is the first study to use ANNs to predict trauma volumes and severity across multiple trauma centers. Unique to this study, we have performed a larger study by incorporating multiple trauma centers into the model. We intentionally chose level one centers of varying volume and mechanism of injury. Additionally, we chose centers with wide geographic and climate variation in an attempt to validate the broad applicability of this methodology.

Our results show that, while trauma volume may vary across centers, patterns emerge that are similar across all centers. As a whole, Figures 2–4 suggest that while volume may vary greatly from center to center, the overall relative temporal patterns are similar across centers. Weekday mornings are relatively low volume times for all trauma centers included in the study. Conversely, evenings and weekends are high volume times for trauma centers. Figure 5 shows relative trauma volume as a function of day of the year. Variation exists between trauma centers, but a general pattern emerges in which the warmer months are higher volume times, giving credence to the anecdotally identified “trauma season.”

The ANN performed well across all centers but did have some variability between the centers. Correlation coefficients increased as trauma admission volume increased. This general trend is likely related to sample sizes from the various centers. Similarly, we noted higher correlation coefficients with higher volume days as compared to lower volume days. The lone exception was Rochester, which had the highest correlation coefficient but the fourth highest admission volume. It is not entirely clear why Rochester performed best in the model despite not being the highest volume center. The correlation coefficient for Rochester was only slightly higher than for Houston and Nashville. This suggests there was currently unidentified subtle pattern to trauma admissions at that center that allows it to more closely align with the model. The correlation coefficients are similar enough between the centers to be considered essentially the same. These findings suggest this ANN may be useful in identifying periods of increased needs for trauma centers.

Relative to our previous studies, we continue to refine the ANN. As demonstrated in Figure 1, we created a new input variable for the specific trauma center. Also, we included more weather data, specifically low temperatures and snow, as inputs into the model. Due to variations in data submitted by the different trauma centers, we were unable to standardize the data in way that would allow for prediction of operative case volume. The model accounts for holidays that occur on the same day each year (e.g. Independence Day, Halloween, Christmas, etc.) by virtue of the fact that they do occur on the same day each year. Holidays that occur on different dates each year (e.g. Memorial Day, Labor Day, Thanksgiving) are slightly more difficult to account for but ultimately average out over time as these holidays occur on different dates but within the same basic calendar window from year to year. We used a 3-year admission sample to account for this variability in our model. Local holidays and "one-off" events like disaster events or unique celebration events are inherently difficult to predict. Inclusion of these events would serve to reduce the broader applicability of the model and were not included.

The predictive ability of this model has obvious implications from a resource and personnel allocation perspective. Its ease of use and high reliability, especially in periods of higher than usual volume, make it a potentially attractive tool for hospital administrators. It can easily be incorporated into a web-based tool that would allow hospitals to predict times of increased staffing and resource needs. Weather forecasts from any source can be used to make predictions. The predictive application of this model can also be used to inform trauma service workflows, including shift changes and handoffs. Periods of relative low admission volume during the day could be used by nursing staff to perform essential tasks for patients already admitted. For physicians, this information may be useful in optimizing educational opportunities such as rounding and didactic lectures. This tool may provide valuable information to perioperative teams in identifying optimal times for inpatient procedures. On a broader scale, the seasonal variability could potentially inform organizations of ideal times for scheduling periods of necessary increases in staffing.

There are some notable limitations to our model that warrant special mention. Weather data was input based on actual measurements, not predictions. To maximize the predictive value of the model, prospective predictions using weather forecasts would be beneficial. Our model shows a high level of internal reliability for the centers included in the study. And while we intentionally chose trauma centers that had variability in volume, mechanism of injury, climate and geography, this model has not yet shown itself to be a viable mechanism for predicting trauma volume or acuity at a new center that has not provided admission data. Therefore, the application of its predictive ability to other centers, especially level 2 and 3 centers, is not possible at this time. However, this study does show that incorporating data from other trauma centers into the model can result in predictive data that remains highly reliable. As previously mentioned, variations in data submissions from the participating centers prevented us from predicting operative needs for trauma admissions in this study. This is an important prediction for resource allocation at the broader hospital level if the tool is to be used by hospital administration. As with our previous study, there is no distinct comparator for this type of prediction model. It is not clear exactly what level of accuracy, in terms of correlation coefficient, is required to optimize resource utilization. Lastly, the overall model is an averaging of the predictability at each center. Other modeling architectures might allow for training of an institution-specific neural network that incorporates additional local factors (e.g. local events, school system holidays, trauma diversion, etc.) not included in our model.

Conclusion

An artificial neural network can predict trauma admissions and severity of injury with high degree of accuracy across a variety of disparate trauma centers. Weather and trauma center admission data as primary inputs result in a model that demonstrates seasonal variation that correlates with increased volume during warmer times of the year. Admission volumes vary by trauma center but all follow a similar pattern of higher admission volumes at night and on weekends. Higher volumes correlate with more accurate predictive ability of the ANN. This model can be used to inform trauma centers of peak times of trauma admissions which can help optimize workflows, staffing needs and resource utilization.

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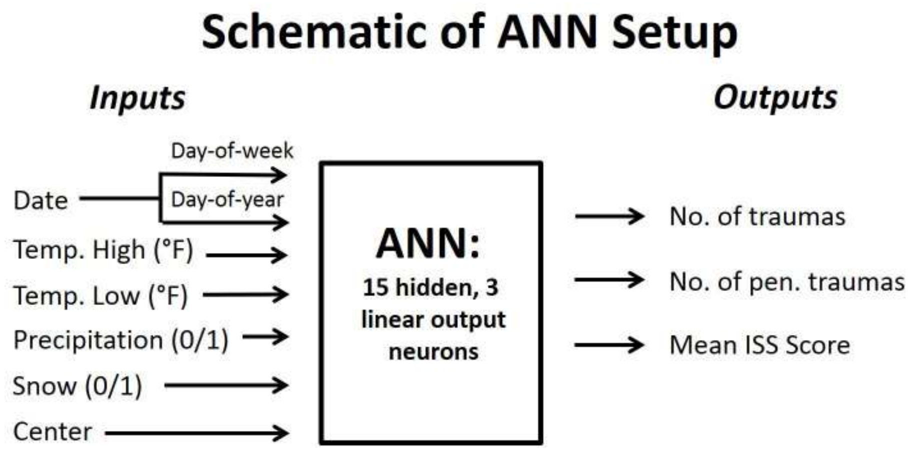

Figure 1.
Schematic of ANN Setup.

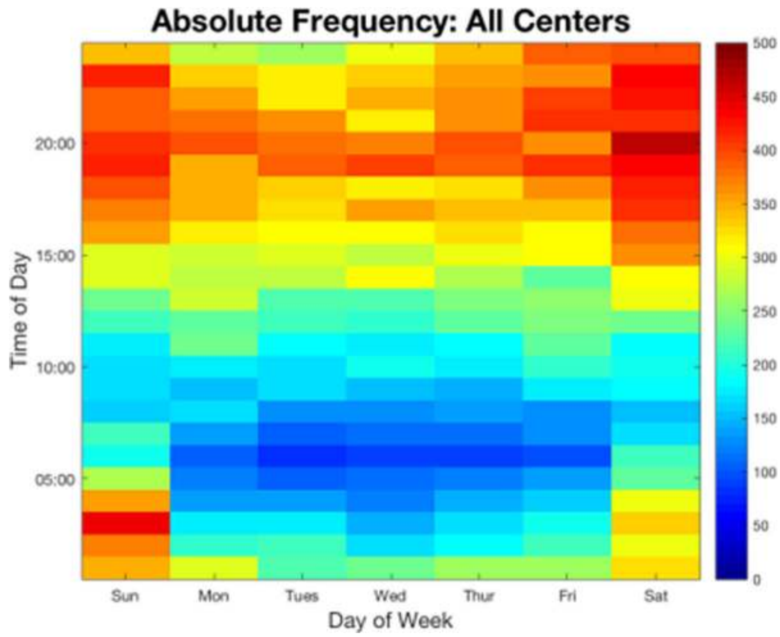

Figure 2.
Heatmap for all trauma centers combined showing absolute frequency of trauma admissions by time of day (y-axis) and day of week (x-axis).

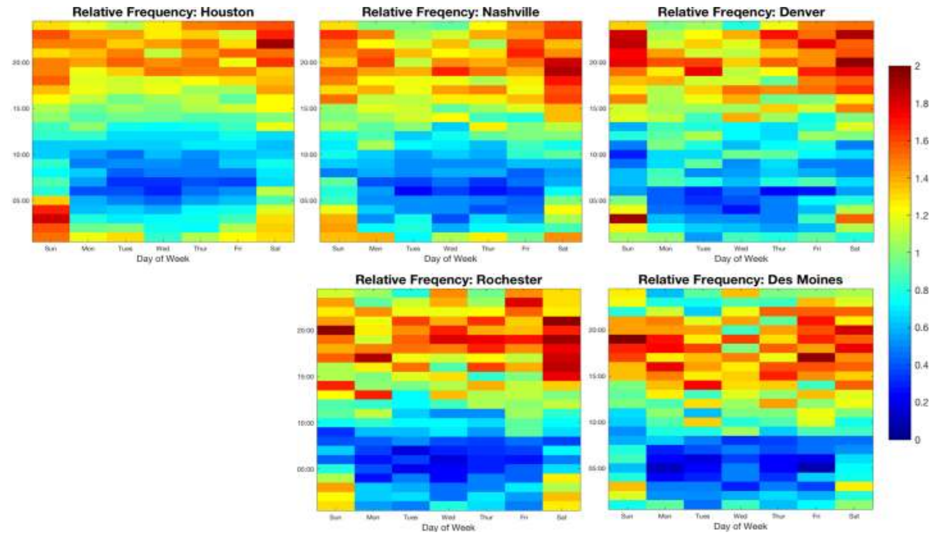

Figure 3.

Heatmap from each trauma center showing relative frequency of admissions by time of day (y-axis) and day of week (x-axis).

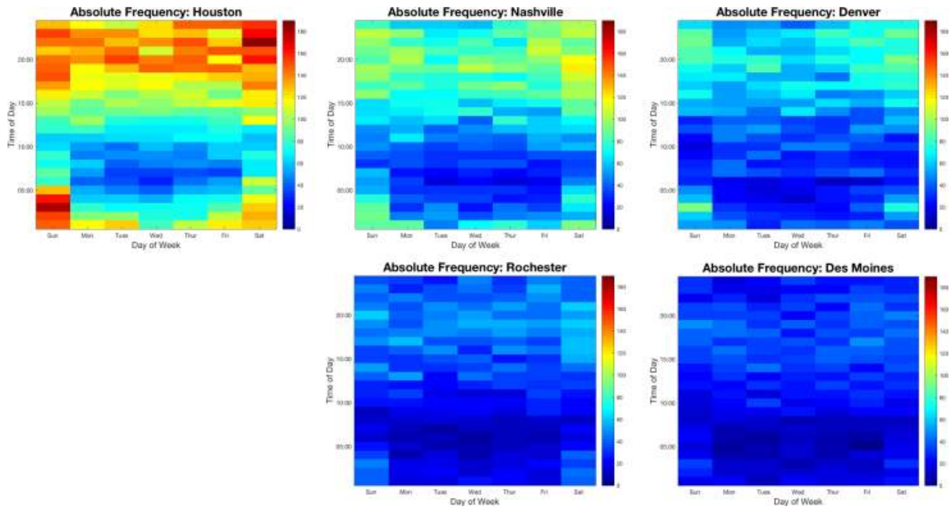

Figure 4.

Heatmap from each trauma center showing absolute frequency of admissions by time of day (y-axis) and day of week (x-axis).

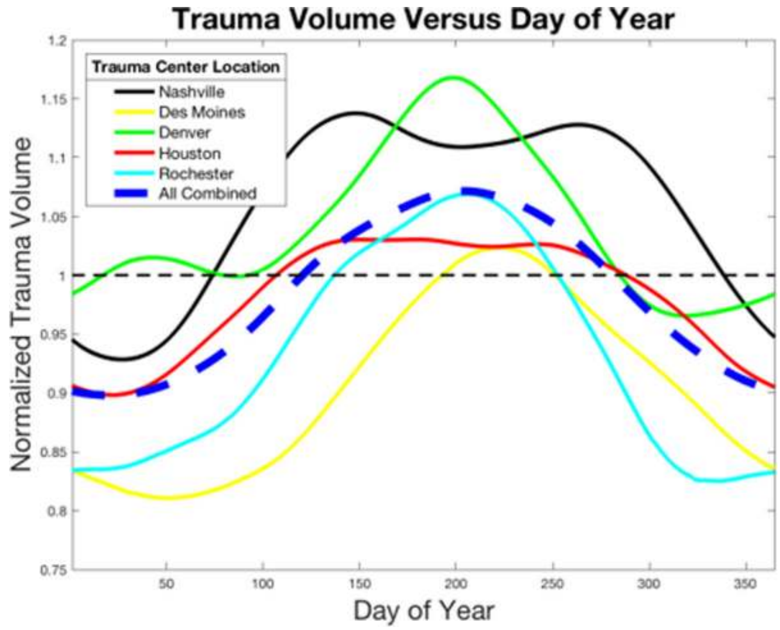

Figure 5.

Relative trauma volume (y-axis) as a function of day of the year (x-axis) for each trauma center and for all centers combined (dotted blue line). Black dotted line represents daily median number of trauma for each center. All fit lines smoothed using LOWESS.

Table 1.

Training output data for each center.

	Houston	Nashville	Denver	Rochester	Des Moines
Mean No. Trauma Contacts/day	15.0 (SD 4.9)	9.8 (SD 3.9)	6.4 (SD 2.9)	4.8 (SD 2.6)	3.7 (SD 2.2)
Mean No. Penetrating Traumas/day	1.3 (SD 1.3)	1.2 (SD 1.2)	1.0 (SD 1.1)	0.8 (SD 1.4)	0.2 (SD 0.4)
Mean ISS	11.6 (SD 2.7)	14.9 (SD 4.3)	10.3 (SD 4.9)	13.0 (SD 9.5)	9.2 (5.2)