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An Early Warning System Using Machine Learning for the Detection of Intracranial Hematomas in the Emergency Trauma Setting

Aydin AYDOSELI[1], Tugrul Cem UNAL[1], Onur KARDES[2], Ozge DOGUC[3], Ilyas DOLAS[1], Ali Ekrem ADIYAMAN[1], Emircan ORTAHISAR[1], Gokhan SILAHTAROGLU[3], Yavuz ARAS[1], Pulat Akin SABANCI[1], Serra SENCER[4], Altay SENCER[1]

[1]Istanbul University, Istanbul Faculty of Medicine, Department of Neurosurgery, Istanbul, Turkey
[2]Beykent University, Department of Computer Engineering, Istanbul, Turkey
[3]Istanbul Medipol University, Department of Management Information Systems, Istanbul, Turkey
[4]Istanbul University, Istanbul Faculty of Medicine, Department of Radiology, Istanbul, Turkey

Corresponding author: Tugrul Cem UNAL ✉ tugrulcem@gmail.com

ABSTRACT

AIM: To present an early warning system (EWS) that employs a supervised machine learning algorithm for the rapid detection of extra-axial hematomas (EAHs) in an emergency trauma setting.

MATERIAL and METHODS: A total of 150 sets of cranial computed tomography (CT) scans were used in this study with a total of 11,025 images. Of the CTs, 75 were labeled as EAH, the remaining 75 were normal. A random forest algorithm was utilized for the detection of EAHs. The CTs were randomized into two groups: 100 samples for training of the algorithm (split evenly between EAH and normal cases), and 50 samples for testing. In the training phase, the algorithm scanned every CT slice separately for image features such as entropy, moment, and variance. If the algorithm determined an EAH on two or more images in a CT set, then the workflow produced an alert in the form of an email.

RESULTS: Data from 50 patients (25 EAH and 25 controls) were used for testing the EWS. For all CTs with an EAH, an alert was produced, with a 0% false-negative rate. For 16% of the cases, the practitioner received an email from the EWS that the patient might have an EAH despite having a normal CT scan. Positive and negative predictive values were 86% and 100%, respectively.

CONCLUSION: An EWS based on a machine learning algorithm is an efficient and inexpensive way of facilitating the work of emergency practitioners such as emergency physicians, neuroradiologists, and neurosurgeons.

KEYWORDS: Artificial intelligence, Machine learning, Epidural hematoma, Subdural hematoma, Trauma

ABBREVIATIONS: AI: Artificial intelligence, **CT:** Computed tomography, **DICOM:** Digital imaging and communications in medicine, **EAH:** Extra-axial hematoma, **EWS:** Early warning system, **RFA:** Random forest algorithm

Aydin AYDOSELI : 0000-0002-4695-8295
Tugrul Cem UNAL : 0000-0001-6228-1379
Onur KARDES : 0000-0002-5342-9316
Ozge DOGUC : 0000-0002-5971-9218
Ilyas DOLAS : 0000-0002-3425-3220
Ali Ekrem ADIYAMAN : 0000-0002-4284-8611
Emircan ORTAHISAR : 0000-0001-9418-6050
Gokhan SILAHTAROGLU : 0000-0001-8863-8348
Yavuz ARAS : 0000-0001-8418-2291
Pulat Akin SABANCI : 0000-0002-0283-0927
Serra SENCER : 0000-0002-3942-093X
Altay SENCER : 0000-0001-9925-5422

INTRODUCTION

In the last decade, increased computation power and developments in programming have allowed wider use of artificial intelligence (AI) systems. In the medical field, many tools using AI have been described including artificial neural networks, supervised and unsupervised machine learning systems, and deep learning algorithms (4). Machine learning, a branch of AI, has the capability of analyzing vast amounts of data via complex algorithms that have the ability to do self-training without the need for any additional programming (12). These algorithms have been used to predict outcomes, analyze data, triage conditions, or achieve a diagnosis.

Neurosurgery is one of the specialties that can benefit immensely from the developments in AI systems (25). Artificial neural networks have been successfully employed for outcome predictions in craniocervical injuries or traumatic brain injury (3,13,19,22). AI systems and machine learning can also be used for analysis of radiologic data. Various radiologic triage tools that depend on AI have been described, such as algorithms detecting intracranial hematomas or critical findings on head computed tomography (CT) scans (8,11,29). The practicality of these systems is still in question because they are far from perfect and still need to be improved substantially.

Early warning systems (EWS) that can flag important pathologies may be beneficial for medical practitioners and patients, especially in an emergency setting. One of the most critical and urgent conditions in a trauma setting is an extra-axial hematoma (EAH). Early diagnosis and prompt intervention are crucial for a better prognosis of EAHs (5,28). An EWS implemented with an algorithm that detects EAHs might decrease the time between admission and diagnosis, thus it can benefit the practitioners and patients. Here, we present an EWS that employs a supervised machine learning algorithm for the detection of EAHs.

MATERIAL and METHODS

In this study, a supervised learning method was used in which the algorithm was provided with the patient's status (EAH or normal) during training. CT scans from 100 patients were used for training. For each patient, 50–120 slices (images) were available, with a total of 11,025 images. Images were provided in Digital Imaging and Communications in Medicine (DICOM) format and each image contained a sliced photo of the patients' cranial CT. These images were used for the training phase. KNIME 4.1, an open-source data processing software system, was used to create a training platform and implement the early warning system. The KNIME system provides a set of tools for image processing, training the algorithm, and evaluating the results.

A total of 150 sets of cranial CTs were used in this study. Half of the CTs were from patients with EAH, the other half were normal controls. The patient demographics are shown in Table I. The thickness of EAHs varied from 5 mm to 49 mm. The CTs were randomized into two groups (Table II). In the first group, cranial CTs from 100 patients (50 EAH, 50 normal) were used to train the machine learning algorithm. The testing phase was performed with the other 50 cranial CTs (25 EAH and 25 normal).

Table I: Patient Demographics

	EAH (n=75)	Normal (n=75)
Age	1-86 (mean: 23.1)	1-91 (mean: 30.3)
Sex (F/M)	25/50	33/42

EAH: *Extra-axial hematoma,* ***F:*** *Female,* ***M:*** *Male.*

Table II: Extra-Axial Hematoma Characteristics

	Training phase (n=50)	Test phase (n=25)
EAH Thickness (mm)	5.2-49.6 (mean:18.9)	5.2-29.1 (mean: 16.1)
EAH side (R/L)	24/26	15/10
EAH location		
Frontal-parietal	36	16
Temporal	9	9
Occipital	5	-

EAH: *Extra-axial hematoma,* ***R:*** *Right,* ***L:*** *Left.*

The training phase consisted of three steps: 1) reading and preprocessing images; 2) extracting labels and partitioning the images; and 3) training the model and evaluating it. When the training phase was completed, the trained model was extracted to be used in the EWS.

Reading and Preprocessing Images

The preprocessing phase applied several transformations to the images to make them more readable and also EAHs more easily identifiable. For example, Figure 1 shows the same image before and after 'normalization' was applied. It can be observed that the image contrast was increased and the EAH became more apparent in the image. In addition to normalization, all images were processed with minimum and maximum filters to reduce noise caused by the background (black) and skull (white). After all extremes were removed from the images, the global threshold was applied to smooth the brain tissue and make the EAH, if present, even more apparent. Figure 1C shows the same image in Figure 1A after the filters and thresholds were applied.

Extracting Labels and Partitioning the Images

The random forest algorithm (RFA) was used for the EWS; and as a supervised learning algorithm RFA required images to be labeled before training (14). For this study, each image was labeled as "Normal" or "EAH." Among the 11,025 images used for training, 5,475 images (75 patients) belonged to patients with an EAH and the remaining 5,550 (75 patients) were labeled as 'Normal'.

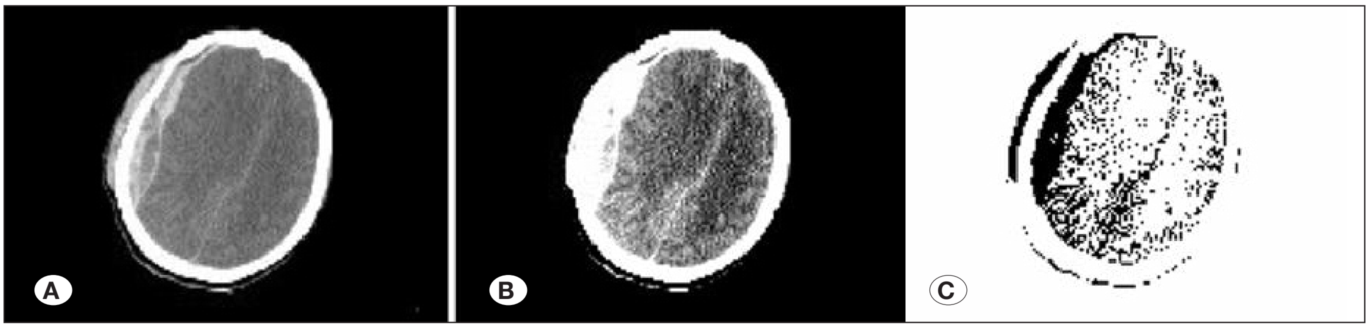

Figure 1: Preprocessing of a CT image: A CT image of a fronto-parietal subdural hematoma **(A)** after application of contrast **(B)** and threshold **(C)** for better detection of the EAH by the algorithm.

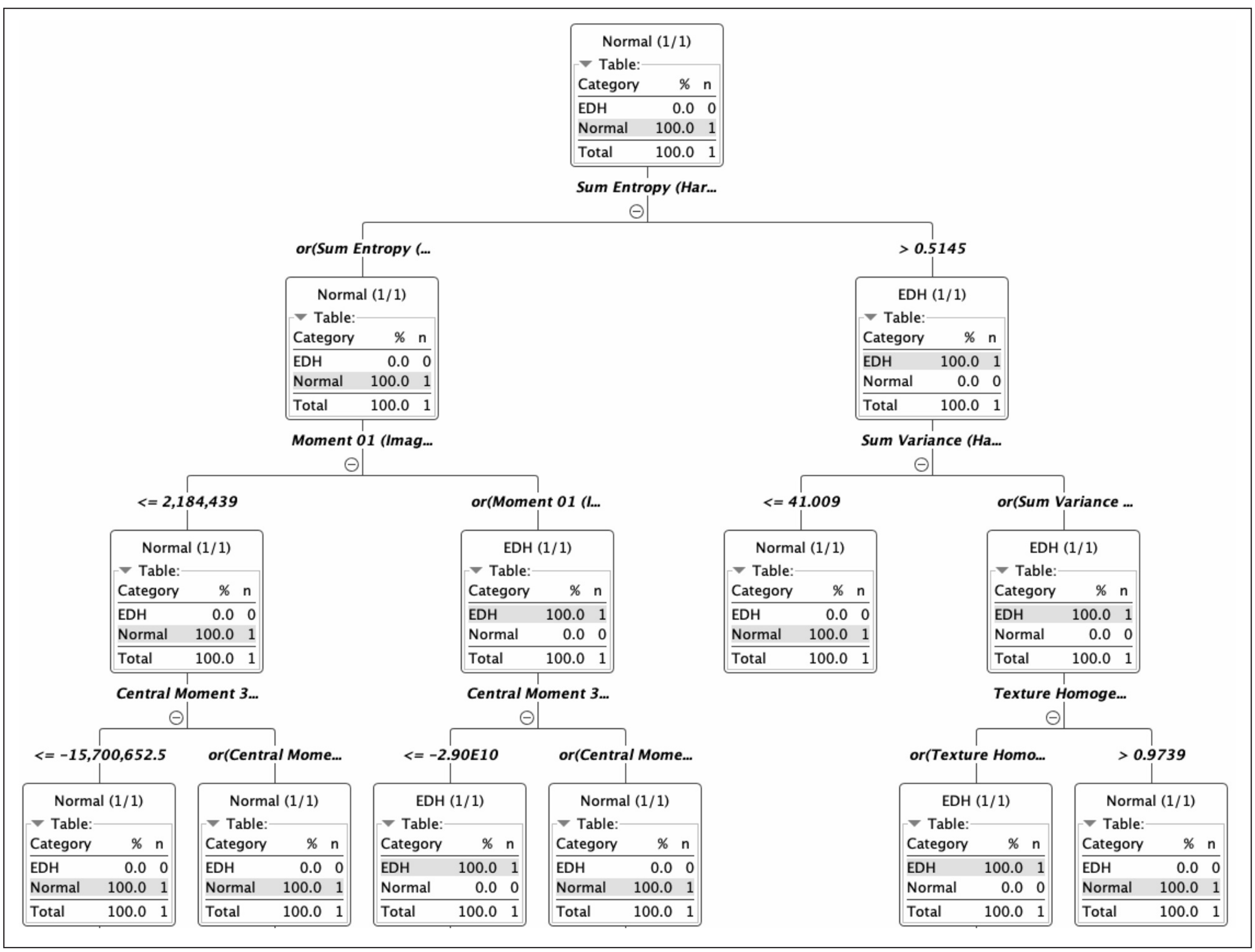

Figure 2: The decision tree of the random forest algorithm.

Training of the Algorithm

The RFA generated a number of decision trees based on the image features and labels that were provided as input and showed probabilities for image features that could be used to make EAH and normal decisions for each image. The RFA splits the input data set into subsets randomly and generates a decision tree for each subset. In the final stage, the RFA measures the variances and chooses the decision tree that provides the best (i.e., the most accurate) results based on the provided labels. In this study, the number of decision trees to be created was capped at 100 for space and time efficiency. Static random seed was used for randomization and Gini Index was used to measure variance.

In this study, the RFA was used to process single images one-by-one instead of processing the entire CT set. Figure 2 shows part of the final decision tree that was generated by the algorithm. According to the decision tree, among the 50 factors evaluated from Haralick Features (30) and image moments (i.e., central, raw, normalized central, and Hu moments); entropy and variance from the Haralick Features, and central moment features in the images were the most effective factors in deciding the label. In image processing, the image moment is a weighted average (moment) of the image pixel intensities, or a function of such moments, usually chosen to have some attractive property or interpretation. Simple properties of the image, which were found via image moments included the area (or total intensity), its centroid, and information about its orientation. Entropy on the other hand, measured the intensity of the image histogram, which showed probabilities of different gray-levels in the image.

Once the decision tree was created, the RFA algorithm scanned the most probable factors consecutively for single images. Using the decision tree and the images in the second (test) partition, the RFA was used to generate predictions as EAH or normal for each image. For each prediction, the RFA also provided a confidence score between 0–100%. In this study, predictions with more than 90% confidence were accepted and the rest were ignored. Figure 3 shows a snippet of predictions and confidence levels generated by the RFA. In that snippet, prediction (normal) for the first image was taken as it had 90% confidence associated with it. Predictions for the other images were ignored as their confidence levels were lower.

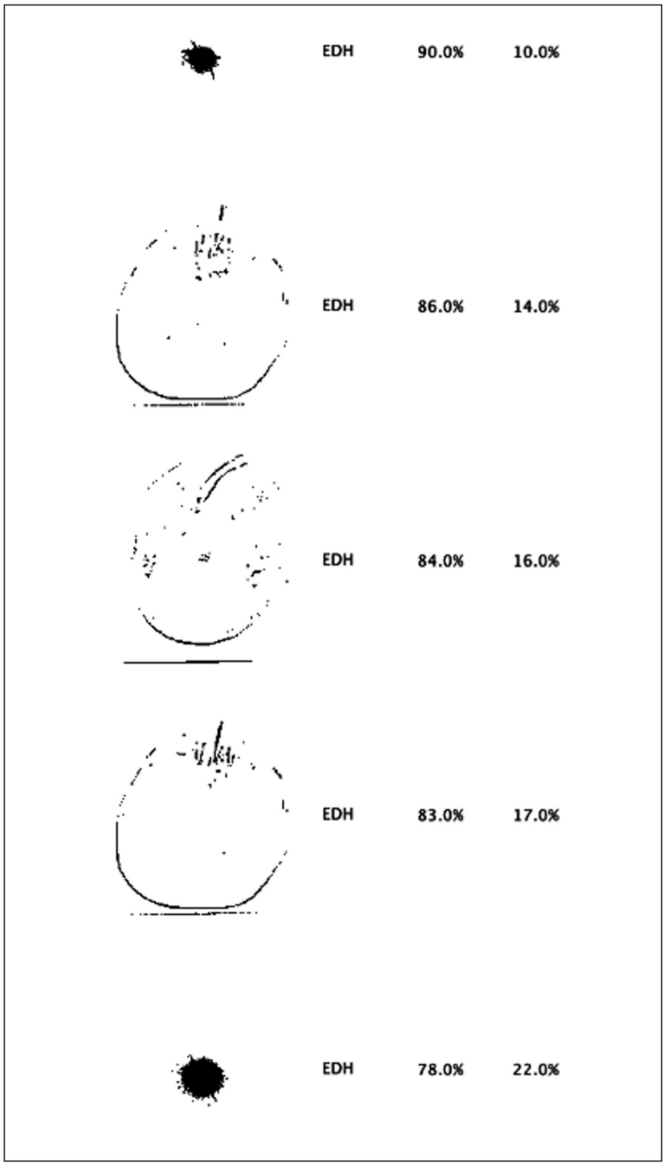

Figure 3: EAH predictions and confidence levels generated by the EWS for different images.

Early Warning System

If the algorithm determined an EAH on 2–10 images in a CT set, then the workflow produced an alert. If the algorithm decided that a set contained more than ten images of EAH then the alert was labeled as high-importance. If an alert was produced, an email was sent to an emergency physician, neurosurgeon, and radiologist at the end of the process. The KNIME workflow for the EWS is represented in Figure 4 and a flowchart is shown in Figure 5.

RESULTS

Data from 50 patients (25 EAHs and 25 controls) were used for testing the EWS. The results for the test runs are provided in Table III. As can be seen in Table 3, all EAH cases were successfully identified by the EWS. For all CTs with an EAH, an alert was produced, with a 0% false-negative rate. In 88% of the cases, the practitioner was informed with a high-importance email. For 16% of the cases, a false-positive alert was produced, meaning that the practitioner received an email from the EWS that the patient might have an EAH despite having a normal CT scan.

Statistical analysis of the results is shown in Table IV. Sensitivity shows the probability that EWS generates an alert when an EAH is present; and the test results showed a 100% success rate. Specificity measures the probability that an EWS does not generate an alert when an EAH is not present. In a few cases, the EWS generated a false alarm, thus the

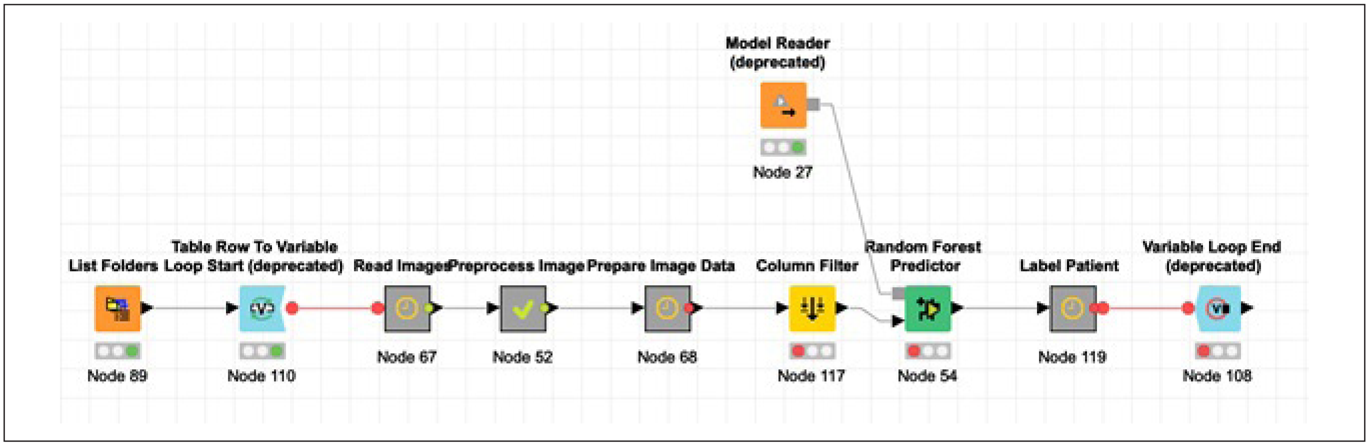

Figure 4: The KNIME workflow for the EWS.

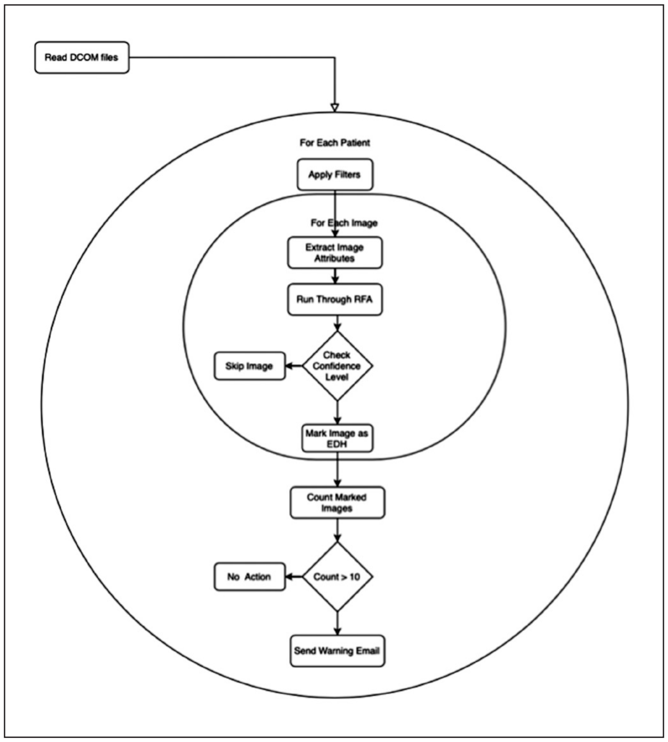

Figure 5: Flowchart of the EWS alerting mechanism.

Table III: Results of the Testing Phase

EWS Decisions	EAH (n=25)	Normal (n=25)
Alert with high importance	22	0
Alert	3	4
No alert	0	21

***EAH:** Extra-axial hematoma, **EWS:** Early warning system.*

Table IV: Statistical Analysis of the Results

Feature	Value	95% CI
Sensitivity	100.00%	86.28% to 100.00%
Specificity	84.00%	63.92% to 95.46%
Positive Likelihood Ratio	6.25	2.55 to 15.34
Negative Likelihood Ratio	0.00	
Disease prevalence (*)	50.00%	35.53% to 64.47%
Positive Predictive Value (*)	86.21%	71.80% to 93.88%
Negative Predictive Value (*)	100.00%	
Accuracy (*)	92.00%	80.77% to 97.78%

specificity of the test results was 84%. Positive and negative likelihood ratios showed the success of the EWS more clearly. A negative likelihood ratio, which is the probability of negative test results in the presence of EAH, was 0% in our testing process with the EWS. Positive and negative predictive values also showed the success of the EWS, which was 86% and 100%, respectively. Finally, the overall accuracy of the EWS; that is, the overall probability that a patient is correctly diagnosed, was calculated as 92%.

DISCUSSION

Machine learning, with many varieties, is the most common AI method in use (18,20). There has been growing interest in machine learning, especially for diagnostics. Various algorithms have been used for the detection of diabetic neuropathy, skin cancers, and pulmonary nodules. Algorithms may also be employed for radiologic detection of various pathologies. Several diagnostic tools using AI have also been published in the field of neurosurgery (7,13,23,24). Dou et al. reported the detection of cerebral micro-hemorrhages using neural networks (9). Arbabshirani et al. described a convolutional 3D neural network prioritizing intracranial hemorrhages in a radiology setting (2). This is the first study in the literature to successfully detect traumatic EAH with a machine learning model, integrated into an EWS.

In this study, we used a supervised learning method that evaluated every slice separately. Supervised learning algorithms learn from labeled training data, which means that every image set must be labeled during the training of the algorithm. In this instance, the labels were "EAH" and "normal." Supervised learning provides a faster training period for algorithms because we were able to train the algorithm with only 100 CT scans compared with thousands of CT scans that are necessary for neural networks to work properly. Contrary to some of the popular studies in the area (10) in which image sets have been processed, this algorithm scans every image separately. Also, training of this algorithm does not require high processing power. Nevertheless, the most important advantage of scanning every image separately seems to be in the decreased number of false-negative results. Our algorithm was able to predict all EAHs presented in the test phase without any false-negative results; the rate of false-positive results was 16%, however. Although this system had a relatively high rate of false-positive results, avoiding false negatives is essential, especially for an EWS designed to work in an emergency trauma setting.

Epidural and acute subdural hematomas are fatal conditions accounting for 8–15% of head injury cases (1,16,21). In cases that require EAH evacuation, a longer duration between admission and intervention is associated with a worse prognosis (5,15,27). In some cases of operative EAHs, for example, patients may demonstrate mild symptoms with an intact neurologic exam (6,26). Up to 57% of epidural hematomas that require emergency evacuation may present in a lucid interval (17). Especially in trauma centers established in high-density population areas, some delay might be expected from admission to the initial treatment. These kinds of diagnostic EWSs may provide faster management of EAHs for practitioners, resulting in improved outcomes.

The EWS scans all the cranial CTs obtained in the trauma center. An instant warning is issued to the attending emergency physician and consultant neurosurgeon via email when an EAH is detected. The system can be reconfigured to use phone calls, SMS, or any social media outlet for issuing a notification to practitioners. The priority of the practitioner can thereby be redirected to more severe conditions. The EWS also notifies the neurosurgeon, thus hastening the duration of the neurosurgical consultation. These EWSs can also be employed in remote trauma centers using a few changes in coding. The purpose of the EWS will then be a quick diagnosis of an intracranial hematoma, thus speeding up the transfer process to a tertiary center with a neurosurgery department.

These algorithms and EWSs can run on any modern device and do not require advanced hardware systems. The EWS is a system that is simple enough for any practitioner to use. It can also be implemented in any emergency department system with a picture archiving and communication system using DICOM images. Despite being a complex system in itself, the EWS does not require any expensive equipment.

The algorithm provided good results in a limited sample size. The sample size used to train the algorithm was relatively small in our study, consisting of 100 head CTs. On the other hand, the algorithm used in our EWS is open to improvement. The accuracy is expected to increase with a larger sample size. Accordingly, we expect a decrease in false-positive results with further training. We included EAHs thicker than at least 5 mm for the training and testing stages because we aimed to focus on clinically relevant EAHs. In addition, the CTs in our study consisted of isolated epidural or acute subdural hematomas. The CTs with additional pathologies, such as contusions, intraparenchymal hemorrhages, and depressed skull fractures, might be implemented on the algorithm with adequate training. Further training with samples of a thin EAH might also produce exact results for even millimeter-thick EAHs.

The purpose of the EWS is to prioritize EAHs in the emergency trauma setting. Although our system did not produce any false-negative results, it had a considerable amount of false-positive results. Additionally, one should be wary of the mistakes that automated systems can make. The practitioner should not rely solely on any EWS. AI diagnostic tools are still not as reliable as an experienced clinician or radiologist.

CONCLUSION

We will witness, in the near future, the emergence of various AI diagnostic tools in the medical field. An EWS based on a machine learning algorithm is an efficient and inexpensive way to facilitate the work of emergency practitioners such as emergency physicians, neuroradiologists, and neurosurgeons.

AUTHORSHIP CONTRIBUTION

Study conception and design: AA, TCU

Data collection: ID, AEA, EO

Analysis and interpretation of results: OK, OD

Draft manuscript preparation: TCU

Critical revision of the article: AA

Other (study supervision, fundings, materials, etc...): GS, YA, PAS, SS, AS

All authors (AA, TCU, OK, OD, ID, AEA, EO, GS, YA, PAS, SS, AS) reviewed the results and approved the final version of the manuscript.

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