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# Intelligent Early Warning System for Epidural Acute Hematomas

*Epidural Akut Hematomlar İçin Akıllı Erken Uyarı Sistemi*

Özge Doğuç*

**Abstract:** Epidural hematoma (EAH) is the accumulation of blood in the space between the outer membrane of the brain (dura mater) and the bone. Acute subdural and epidural hematoma appears on CT scan as a hyper-dense collection often located in brain convexity. Such bleeding can become fatal by increasing intracranial pressure and creating a mass effect. Therefore, it is very important to recognize these bleedings promptly in an emergency trauma setting. Thus, early diagnosis is essential to reduce mortality and morbidity rates in these cases. There has been a growing interest in artificial intelligence (AI) and machine learning (ML) algorithms for diagnostics in medical fields. In this study, a supervised learning method was used in which the decision tree ML algorithm is trained with the patients' statuses (EAH or Normal). This study proposes an early warning system (EWS) that scans all cranial CTs obtained at the trauma center. The EWS in this study, trained with CT scans from about 100 patients, can predict EAH with 100% accuracy using image recognition and supervised learning algorithms. Each MR section obtained for each patient is individually analyzed by image processing and EAH detection is made. For this, the decision tree method, which is a supervised learning algorithm, was trained and used to detect EAH in MR sections. The algorithm has been developed in such a way that it will immediately alert the emergency physician and consultant neurosurgeon by e-mail when it detects EAH in more than 10 sections in any patient.

**Structured Abstract:** Epidural and acute subdural hematomas (EAH) are fatal conditions that consist of more than 50% of head injury cases. (Jack E. Wilberger Jr. M.D., 1991) Promptness is especially important in coping with EAHs. There has recently been a growing interest on artificial intelligence (AI) and machine learning (ML) algorithms for diagnostics in medical fields. In the field of neurosurgery, several diagnostic tools utilizing AI have been published as well.

This study proposes an early warning system (EWS) that scans all cranial CTs obtained in the trauma center. An instant warning is issued to the attending emergency physician and to consultant neurosurgeon via e-mail when the EAH is detected. The EWS uses supervised learning algorithms that can run on any modern device and does not require advanced hardware systems. It also can be implemented in any emergency department system which has a pacs system utilizing DICOM images. Despite being a complex system in itself, the EWS does not require any expensive equipment for hospitals. The purpose of the EWS is prioritizing the EAHs in the emergency trauma setting. Although our system and some others does not produce any false negative results, one should be vary of the mistakes that automated systems can

* Dr. Öğr.Üyesi, İstanbul Medipol Ünüversitesi, İşletme ve Yönetim Bilimleri Fakültesi, Yönetim Bilişim Sistemleri Bölümü
*Asst. Prof. Dr., İstanbul Medipol University, Medipol Business School, Department of Management Information Systems*
ORCID 0000-0002-5971-9218
odoguc@medipol.edu.tr

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make. The practitioner, thus, should not rely solely on EWSs. It is clear that the artificial intelligence diagnostics tools are still not as reliable as an experienced clinician or radiologist is.

In this study, the decision tree ML algorithm has been trained with patients' statuses during training. CT scans from 100 patients have been used for this training. For each patient between 50-120 slices (images) were available, with a total of 7350 images. Images were provided in DICOM format and each image contained a sliced photo of the patients' brain.

Before the pre-processed images are supplied to the learning algorithm, each image has to be labeled. For this study, two labels were used: "Normal" and "EDH". Two folders were created with the same names and training images were placed inside the corresponding folders. All image attributes including their absolute paths were collected in the reading phase, and were extract in this phase, so that the folder names were used as image labels. Among the 7,358 images used for training, 3,607 of belong to patients with EDH and the remaining 3,701 were labeled as 'Normal' as they belonged to patients with no EDH.

Once this labeling was done, all available images were partitioned into 2 sets. The first set contained 70% of the images and were picked randomly. This set was used by the learning algorithm. The second set was used for validation, after learning was done. In this study, the Random Tree Learner (RTL) algorithm was used for training. The RTL algorithm generates a decision tree based on the image features and labels that were provided as input; and shows probabilities for image feature that can be used to make *EDH* and *Normal* decisions for each image. The results show that among the 1048 images from patients with EDH 904 them are correctly labeled by the model (86% accuracy). Similarly, among the 1160 images from patients with no EDH 1002 of them are labeled correctly (also 86% accuracy).

The EWS considers a prediction (EDH or Normal) as *confident*, only if the associated probability (i.e. confidence score) is greater than 90%. This is done to improve the certainty of the predictions and also reduce the number of false alerts. more than 2 images from the same CT set confidently are confidently predicted as EDH, the EWS generates an email alert for the practitioner. EWS also attaches the images that display signs of EDH to the email. If the number of EDH images is more than 10, EWS also marks the email for that set with *high importance.*

For this study, data from 27 patients have been used for testing the EWS. 13 of the patients are eventually diagnosed with EDH; and all EDH cases are successfully identified by the EWS. In 85% of these cases, the practitioner was informed with a *high importance* email. The success rate for the patients with no EDH is also considerable. No high importance alerts were generated and in only 21% of the cases, the practitioner received an email from EWS that the patient might have EDH.

This is the first study in the literature that proposes an early warning system (EWS) that successfully detects traumatic EAH with a machine learning model. The EWS is trained with around CT scans from about 100 patients, can accurately predict EAH through image recognition and supervised learning algorithms. The EWS notifies the practitioners when EAH is detected, and our results showed very small number of false negatives (i.e. missed EAH patients).

**Keywords:** Intelligent systems, epidural hematomas, supervised learning, early warning system, image processing

**Öz:** Epidural hematom (EAH), beynin dış zarı (dura mater) ile kemik arasındaki potansiyel boşlukta kan birikmesidir. Akut subdural ve epidural hematom, BT taramasında genellikle beyin konveksitesinde yer alan hiper yoğun bir koleksiyon olarak görünür. Bu tür kanamalar kafa içi basıncını artırarak ve kitle etkisi yaratarak ölümcül hale gelebilir. Bu nedenle, acil travma ortamında bu kanamaların derhal tanınması çok önemlidir. Bu nedenle bu vakalarda mortalite ve morbiditeyi düşürmek için erken tanı şarttır. Tıbbi alanlarda teşhis için yapay zeka (AI) ve makine öğrenimi (ML) algoritmalarına son zamanlarda artan bir ilgi vardır. Bu çalışmada, karar ağacı ML algoritmasının hastaların durumlarıyla (EAH veya Normal) eğitildiği denetimli bir öğrenme yöntemi kullanılmıştır. Bu çalışma, travma merkezinde elde edilen tüm kraniyal BT'leri tarayan bir erken uyarı sistemi (EWS) önermektedir. Bu çalışmadaki EWS, yaklaşık 100 hastadan alınan CT taramaları ile eğitilmiştir, görüntü tanıma ve denetimli öğrenme algoritmaları ile %100 doğrulukla EAH'yi tahmin edebilir. Her hasta için elde edilen her MR kesiti teker teker görüntü işleme analizinden geçirilir ve EAH tespiti yapılır. Bunun için bir denetimli öğrenme algoritması olan karar ağacı yöntemi eğitilerek MR kesitlerinde EAH saptaması için kullanılmıştır. Algoritma herhangi bir hastada 10'dan fazla kesitte EAH

tespit ettiğinde acil durum hekimine ve danışman beyin cerrahına e-posta ile anında uyarı verecek şekilde geliştirilmiştir.

**Anahtar Kelimeler:** Akıllı sistemler, epidural hematom, denetimli öğrenme, erken uyarı sistemi, görüntü işleme

## Introduction

Epidural and acute subdural hematomas (EAH) are fatal conditions that consist of more than 50% of head injury cases. (Jack E. Wilberger Jr. M.D., 1991) Promptness is especially important in coping with EAHs. In cases that require hematoma evacuation, longer duration between admission and intervention in EAH is associated with worse prognosis. In some cases of operative epidural hematomas, patient may demonstrate mild symptoms with an intact neurologic exam. Epidural hematoma's mortality rate is close to zero if intervened in a timely manner. Especially in trauma centers established in high population density areas, some delay might be expected from the admission to initial treatment. Diagnostic early warning systems (EWS) may provide a fast reaction ability for the practitioners.

There has recently been a growing interest on artificial intelligence (AI) and machine learning (ML) algorithms for diagnostics in medical fields. These algorithms have been used for detection of diabetic neuropathy, skin cancers and pulmonary nodules. In the field of neurosurgery, several diagnostic tools utilizing AI have been published as well. Recently, Dou et al. have reported detection of cerebral microhemorrhages using neural networks. (Dou & al., 2016) This is the first study in the literature successfully detecting traumatic EAH with a machine learning model and implementing an EWS.

In this study, a supervised learning method is used, where the decision tree ML algorithm has been trained with patients' statuses (EAH or Normal) during training. CT scans from 100 patients have been used for this training. Images are provided in DICOM format and each image contains a sliced photo of the patients' brain. For each patient between 50-120 slices (images) are available, with a total of 7,350 images. Knime 4.1, an open source data processing software system has been used to create the training platform and implement the early warning system. KNIME software provides a set of tools for image processing, learning algorithm and evaluating the results. Source code for training and evaluation are available online. [1]

## Literature Survey

Utilization of AI is becoming more prominent in the medical field. Convolutional 3D learning methods that utilize volumetric radiologic data have been used in the literature. Also, neural networks and unsupervised machine learning methods have been implemented for diagnostic purposes. (Kermany DS, 2018) (H. J. Schneider, 2011) In addition, AI including deep learning technology has found significant application areas in the medical imaging domain due to its ability of feature extraction from images (Hamet & Tremblay, 2017) (Obermeyer & E.J., 2016) (Gencturk, Nabiyev, Ustubioglu, & Ketenci, 2013). Deep learning has also been applied in radiotherapy (Meyer, Noblet, Mazzara, & Lallement, 2018), in PET-MRI attenuation correction (F. Liu, 2018), in radiomics (J. Lao, 2017) and for theranostics in neurosurgical imaging, combining confocal laser endomicroscopy with deep learning models for automatic detection of intraoperative CLE images (M. Izadyyazdanabadi, 2018).

In some studies, deep learning has been employed to detect and differentiate bacterial and viral pneumonia in pediatric chest radiographs (Kermany DS, 2018) (Rajaraman S, 2018) Harald J. Schneider et al. also studied about acromegaly recognition using automated face classification

[1] EWS source code is available to download on Github (https://github.com/ozgedoguc/EWS/)

through deep learning techniques (H. J. Schneider, 2011). There are also a few studies about other syndromes beside Down syndrome (S.L. Hartmut, 2003) (Landry, Raiside, & Vanhoutte, 1979).

These are just a few examples of the many applications of deep learning in medical imaging. Other applications of deep learning include clinical radiology (J.-G. Lee, 2017), neuroimaging and neuroradiology (G. Zaharchuk, 2018), brain segmentation (Z. Akkus, 2017), stroke imaging (E.-J. Lee, 2017), neuropsychiatric disorders (S. Vieira, 2017), breast cancer (J. R. Burt, 2018), chest imaging (Ginneken, 2017), imaging in oncology (O. Morin, 2018), and medical ultrasound (L.J.Brattain, 2018).

In this study, a supervised learning method is used. In the literature, supervised learning methods are preferred over deep learning when available data can be tagged or labeled to guide the AI algorithm provide more accurate predictions. Especially, applications in the laboratory testing and imaging areas make use of the high accuracy rate that the supervised learning methods offer. These applications often contain data labels (e.g. test results categories, patient statuses) that are effectively used in supervised learning. (Deo, 2015) The biggest and foremost advantage of this method is that, unlike similar studies in the literature, the method used in the study considers each scan image separately to reduce false negatives significantly. Avoiding false negatives are essential especially for an early warning system designed to work in the emergency trauma setting.

**Problem Definition**

Epidural hematoma is the accumulation of blood in the potential space between outer membrane of the brain (dura mater) and the bone. The dissection between dura mater and the bone creates the space for bleeding. Rapidly clotting bleeding occurs with the disruption of the vessels due to high energy impact. Acute subdural hematoma is the clotting blood collection under the dura but external to the arachnoid membrane of the brain. After a high-energy trauma, blood vessels connecting cortical surface of the brain and dural venous sinuses might tear and result in a subdural bleeding. Cortical arteries and veins may also be disrupted due to trauma. Acute subdural and epidural hematoma appears on CT scan usually as a hyperdense collection located in brain convexity.

These types of bleeding may become fatal by increasing the intracranial pressure and creating a mass effect. If the hematomas reach a certain size, they may lead to pathologic shifts of brain tissue known as herniations, which are highly fatal. Therefore, it is crucial to promptly recognize these bleedings in the emergency trauma setting. Early neurosurgical consultation facilitates prompt intervention of these hematomas if needed. Thus, early diagnosis is essential for lowering the mortality and morbidity in these cases. (Seelig JM, 1984)(Seelig JM B. D., 1981)

**The Early Warning System (EWS)**

This study proposes an EWS that scans all cranial CTs obtained in the trauma center. An instant warning is issued to the attending emergency physician and to consultant neurosurgeon via e-mail when the EAH is detected. The system can be reconfigured for utilizing phone calls, SMS, or social media for issuing notifications to practitioners. The priority of the practitioner thereby can be redirected to more severe conditions. The EWS also notifies the neurosurgeon thereby it hastens the duration of the neurosurgical consultation.

The EWS uses supervised learning algorithms that can run on any modern device and does not require advanced hardware systems. It also can be implemented in any emergency department system which has a pacs system utilizing DICOM images. Despite being a complex system in itself, the EWS does not require any expensive equipment for hospitals.

The purpose of the EWS is prioritizing the EAHs in the emergency trauma setting. Although our system and some others does not produce any false negative results, one should be vary of the mistakes that automated systems can make. The practitioner, thus, should not rely solely on EWSs. It is clear that the artificial intelligence diagnostics tools are still not as reliable as an experienced clinician or radiologist is.

**Methodology**

The image processing method that is used in this study is two-fold: Learning through a large set of data, and making determinations based on the learnt model. The learning phase is also called as ‘training’; as the system is being trained in a way similar to human brain training.

There are two types of learning methods in the literature: unsupervised and supervised learning. In unsupervised learning method, the learning algorithm is trained with available input data and expected to derive output with no assistance. On the other hand, in supervised learning, the method is fed (or supervised) with extra information (i.e. labels or a class variable) to assists the training outcome. In this study, supervised learning method is used, where the algorithm was provided with patients’ statuses (EDH or Normal) during training. This allowed faster and more accurate training results with limited data.

In this study CT scans from 100 patients are used for training. For each patient between 50-120 slices (images) were available, with a total of 7350 images. Images were provided in DICOM format and each image contained a sliced photo of the patients’ brain. Figure 1 shows a sample from one of the patients.

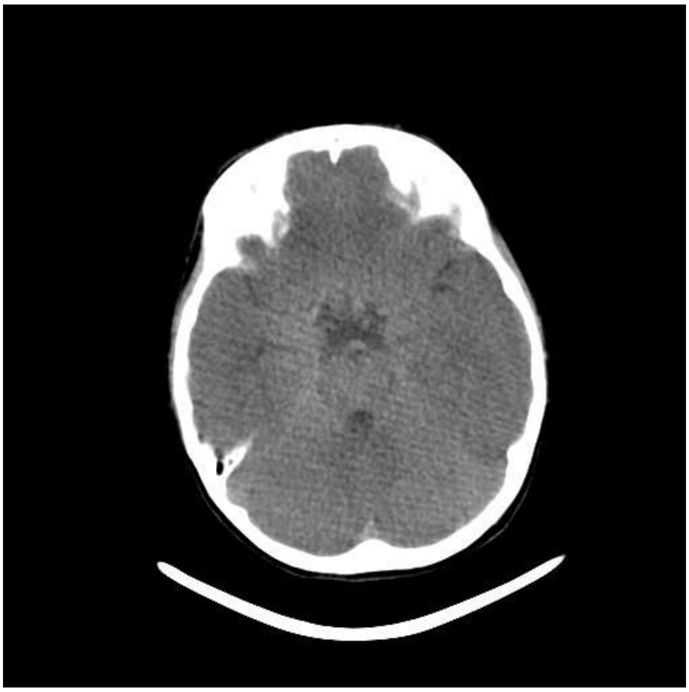

**Figure 1:** Sample Sliced Photo of Patient's Brain

In this study, Knime 4.1[2] system was used to create training platform and implement the early warning system. Knime system provides a set of tools for image processing, learning algorithm and evaluating the results. This section describes the methodology that is set up through the Knime system in detail.

[2] KNIME available for download at https://www.knime.com/downloads/download-knime

**Training Phase**

The training phase consists of 3 steps: 1- Reading and preprocessing images; 2- Extracting labels and partitioning the images; 3- Learning the model and evaluating it. When the training phase is completed, the learnt model is extracted to be used in the 'intelligent early warning system' that was described earlier.

**Reading and Preprocessing Images**

As mentioned earlier, patients' CT results are provided as a set of DICOM images. Although Knime provides nodes for reading and working with images, performance degrades considerably when using the DICOM format. For that reason, the DICOM images have been converted to JPEG as a first step. A python script has been used for this purpose. Figure 2 shows the setup created in Knime for reading the DICOM images and converting them to JPEGs. During this process, file attributes of the images are also stored; as they are used for labeling the images later.

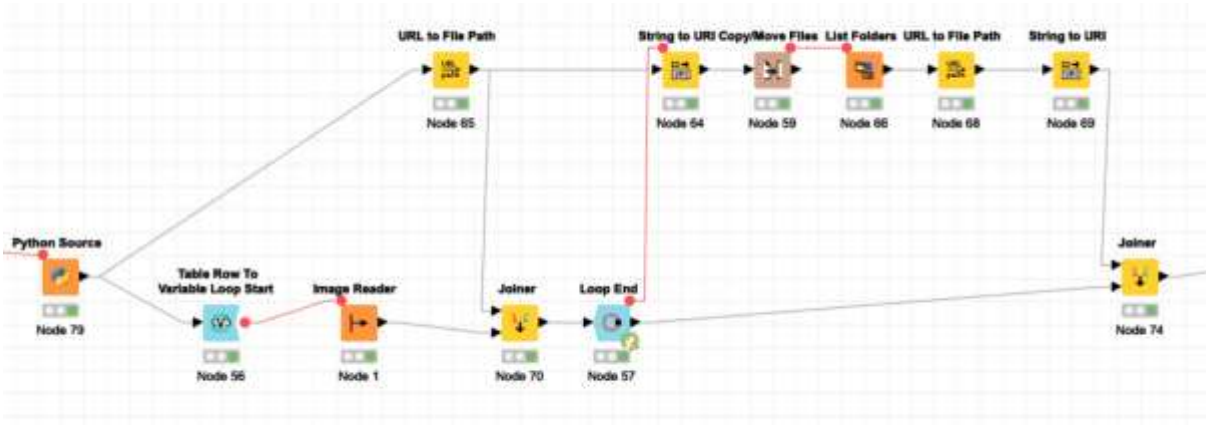


**Figure 2:** Reading DICOMs and Converting Them to JPEGs

The pre-processing phase applies a number of transformations to the images to make **EDH** more easily identifiable. For example, Figure 3 shows the same image before and after the 'normalization' step was applied. It can be observed that the image contrast has been increased and **EDH** has become more apparent in the image.

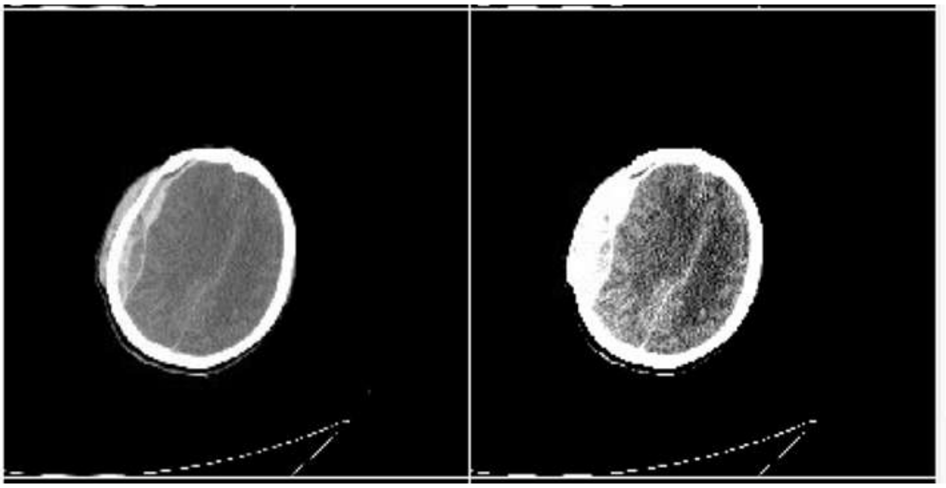

**Figure 3:** Image Before and After Normalization

In addition to normalization, all images are processed with min and max filters to reduce noise caused by the background (black) and the skull (white). After all extremities were removed from the images, the Global Thresholder has been applied to smoothen the brain tissue and make the EDH (if present) even more apparent. Figure 4 shows the same image in Figure 3 after the filters and thresholding is applied. EDH can easily be observed on the top left corner as a dark region. In the image the skull and the background have been removed, and the brain tissue has also been mostly smoothened.

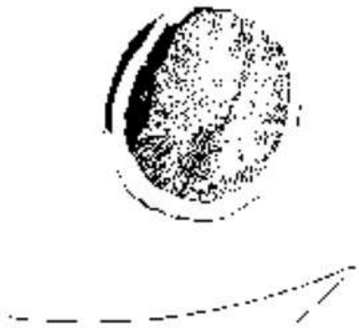

**Figure 4:** Same Image After Pre-processing

As the last step of the pre-processing phase, image features are extracted and converted to numeric attributes; so that the learning algorithm generate associations and derive rules between images and patients based on these attributes. Figure 5 shows the setup created in Knime for pre-processing the images.

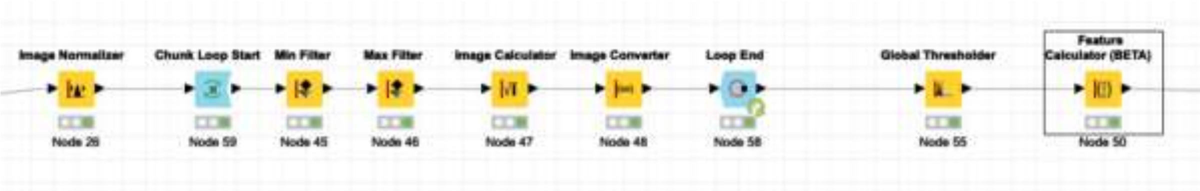


**Figure 5:** Knime Setup for Pre-processing the Images

**Extracting Labels and Partitioning the Images**

Before the pre-processed images are supplied to the learning algorithm, each image has to be labeled. For this study, two labels were used: “Normal” and “EDH”. Two folders were created with the same names and training images were placed inside the corresponding folders. All image attributes including their absolute paths were collected in the reading phase, and were extract in this phase, so that the folder names were used as image labels. Among the 7,358 images used for training, 3,607 of belong to patients with EDH and the remaining 3,701 were labeled as ‘Normal’ as they belonged to patients with no EDH.

Once this labeling was done, all available images were partitioned into 2 sets. The first set contained 70% of the images and were picked randomly. This set was used by the learning algorithm. The second set was used for validation, after learning was done. Figure 6 shows the Knime setup that was created for labeling the images and creating 2 partitions.

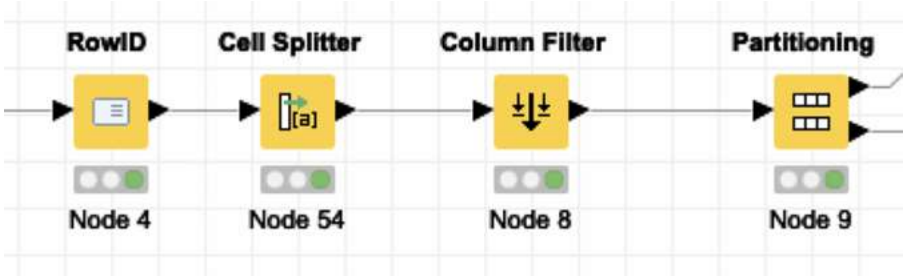


**Figure 6:** Label Extraction and Partitioning

### Learning and Evaluation

In this study, the Random Tree Learner (RTL) algorithm was used for training. The RTL algorithm generates a decision tree based on the image features and labels that were provided as input; and shows probabilities for image feature that can be used to make *EDH* and *Normal* decisions for each image. Figure 7 shows part of the decision tree that is generated by the algorithm. According to the decision tree, Entropy, Moment and Variance features in the images are among the most effective factors in making decisions.

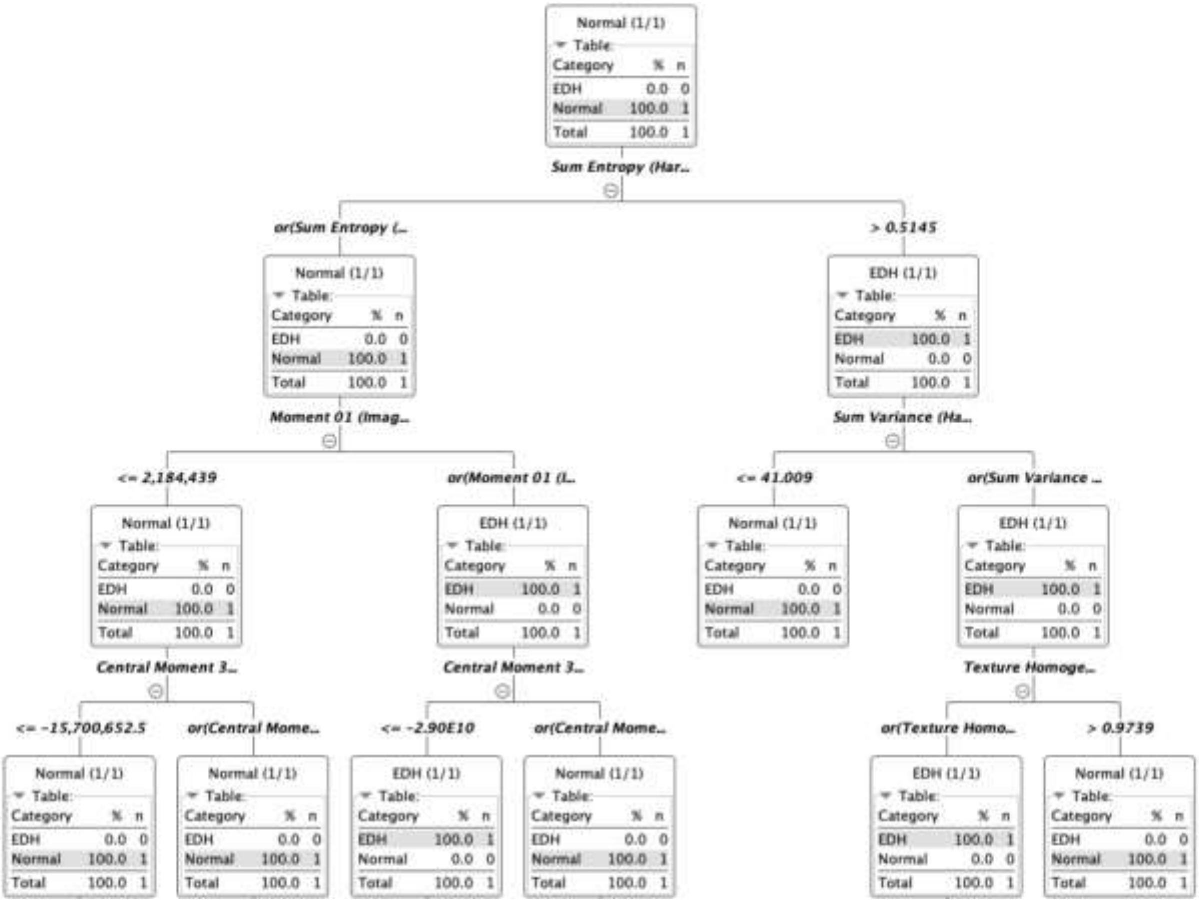

**Figure 7:** Part of the Decision Tree Generated by the RTL Algorithm

As mentioned earlier, the training data set was split into two partitions and the second partition was used to evaluate the results. Using the decision tree shown in Figure 7 and the CT images in the second partition, the RTL algorithm is used to generate predictions for each image. Figure 8 shows the accuracy results of the learnt model.

| Prediction ... | EDH | Normal |
|---|---|---|
| EDH | 904 | 144 |
| Normal | 158 | 1002 |

Correct classified: 1,906 Wrong classified: 302

Accuracy: 86.322 % Error: 13.678 %

Cohen's kappa (κ) 0.726

**Figure 8:** Evaluation of the Learnt Model

The results show that among the 1048 images from patients with EDH 904 them are correctly labeled by the model (86% accuracy). Similarly, among the 1160 images from patients with no EDH 1002 of them are labeled correctly (also 86% accuracy).

**Early Warning System (EWS)**

The early warning system (EWS) which is designed in this study exploits the image processing and learning methods described in the previous section. EWS is designed to assist the practitioners by providing probabilistic decisions for existence of a possible EDH given a patient’s set of CT scans. EWS continuously checks for new CT sets and sends emails to the practitioners with its own predictions regarding the patients’ statuses.

EWS has also been created using the Knime 4.1 system. It first converts the DICOM images to JPEG and runs them through the pre-processing phase similar to the in the Training phase. After the RTL algorithm provides the predictions, the EWS filters them first and then generate email alerts if needed.

The RTL algorithm provides a prediction for each CT image and associates a probability to the prediction. The EWS considers a prediction (EDH or Normal) as *confident,* only if the associated probability (i.e. confidence score) is greater than 90%. This is done to improve the certainty of the predictions and also reduce the number of false alerts. more than 2 images from the same CT set confidently are confidently predicted as EDH, the EWS generates an email alert for the practitioner. EWS also attaches the images that display signs of EDH to the email. If the number of EDH images is more than 10, EWS also marks the email for that set with *high importance.*

**Results**

For this study, data from 100 patients have been used from training, and 27 patients have been used for testing the EWS. During testing, 13 out of 27 patients were eventually diagnosed with EDH. Results for the test runs are provided in Table 1.

**Table 1: EWS Test Results**

| EWS Test Results (27) | **Actual**: EDH | **Actual**: Normal | |
|---|---|---|---|
| **Predicted**: EDH (High Importance) | 11 | 0 | 11 |
| **Predicted**: EDH (Low Importance) | 2 | 3 | 5 |
| **Predicted**: Normal | 0 | 11 | 11 |
| | 13 | 14 | |

As it can be seen in Table 1, all EDH cases are successfully identified by EWS. In 85% of these cases, the practitioner was informed with a *high importance* email. The success rate for the patients with no EDH is also considerable. No high importance alerts were generated and in only 21% of the cases, the practitioner received an email from EWS that the patient might have EDH.

## Conclusion

There has been a growing interest on AI and ML recently in terms of diagnostics in medical fields. A number of algorithms are used for detection of diabetic neuropathy, skin cancers and pulmonary nodules. In the field of neurosurgery, several diagnostic tools utilizing artificial intelligence have been published. This is the first study in the literature that proposes an early warning system (EWS) that successfully detects traumatic EAH with a machine learning model. The EWS is trained with around CT scans from about 100 patients, can accurately predict EAH through image recognition and supervised learning algorithms. The EWS notifies the practitioners when EAH is detected, and our results showed very small number of false negatives (i.e. missed EAH patients).

The sample size used for the training of the algorithm was relatively small in our study, consisting of 100 head CTs. Nevertheless, the algorithm used in our EWS is open to improvement. The model has provided accurate results despite limited sample size. The accuracy is expected to increase with a larger sample size, we thereby expect a decrease in false positive results with further training. We have used EAHs thicker than at least 5mm for the training and testing stages, as we aimed to focus on clinically relevant EAHs. Further training of the algorithm with samples of thin EAH might also produce exact results for even millimeter thick EAHs.

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