# Using the Case-Based Reasoning-YOLO Approach for Rapid and Effective Identification of Bruises

**Haitham Saleh**
Industrial and Systems Engineering Department
Interdisciplinary Research Center for Smart Mobility and Logistics
King Fahd University of Petroleum and Minerals
Dhahran 31261,
Saudi Arabia
haithamhs@kfupm.edu.sa

## Abstract

Bruises can appear when blood vessels rupture, which can lead to the risk of blood leakage into the surrounding tissues. Evaluation and detection of these symptoms, especially those related to health problems or accidents, are very important in medical environments. Bruises can also serve as an alert sign of health problems that a medical evaluation is recommended and might be urgently needed. Unfortunately, it can be very challenging for medical practitioners to appropriately identify and categorize bruises due to the complexity of the situations and many types of bruises. The main goal of this study is to promote the use of Artificial Intelligence (AI) in healthcare systems. It aims to help improve computer-aided practices by making use of an open-source algorithm such as YOLOv8 and incorporate it into a case-based reasoning (CBR) approach for fast and precise identification of bruises. In this study, we introduce an approach to this problem by using the CBR-YOLO approach. The use of the CBR-YOLO approach can help and support the decision-making practice. Although bruises have many types and the same appearance, it can still provide recommendations and commentary on the bruises. This method can be useful in diagnosing patients in a timely manner.

## Keywords
Case-based reasoning, YOLO, automated bruise detection, decision-making, decision support system.

## 1. Introduction
Bruises, the condition is also known as ecchymosis (Hartley et al. 2023), occurs when the blood vessels get ruptured. As a result, blood can leak into surrounding tissues. In medical contexts, the identification and evaluation of symptoms is of the highest significance since symptoms can serve as possible markers of underlying injuries or physical disorders. Symptoms may also act as potential indicators of psychological or health issues in general. Bruises are another potential reason for additional medical testing recommended. The process of visually detecting and classifying bruises may be challenging for healthcare professionals since they frequently require a large degree of expertise in addition to the use of the individual's personal sense of judgment.

Due to recent advances in computer vision and machine learning techniques, it is now feasible to automate the process of analyzing and identifying bruises. In this work, we present an Intelligent Decision Support System (IDSS) that makes it possible to automatically recognize bruises on the human body. This is accomplished by utilizing the most recent iteration of the object identification approach known as You Only Look Once (YOLO) (Jocher et al. 2023) and then, it uses Case Based Reasoning CBR approach (Watson and Marir 1994) to search for the most similar cases in a database and provide suggestions based on the solutions of those cases. This methodology is intended to assist medical personnel, such as medical practitioners and nurses, in recognizing and assessing bruises in a timelier manner, thus improving the accuracy and objectivity of diagnosis. Consequently, this leads to improved patient care, reducing the time it takes to identify an injury, and avoiding the repercussions brought on by misdiagnosed or undiscovered injuries are all possible outcomes of introducing automated bruise recognition into clinical procedures and workflow.

YOLO, the model and the detection system are explained by (Redmon et al. 2016), is an object detection algorithm that utilizes learning to identify objects, in images or videos. It stands out as a one-stage detection algorithm that prioritizes regression concepts resulting in more efficient performance compared to algorithms. YOLO finds applications across domains like image classification, endoscopic image recognition, vehicle recognition, and polyp detection (Nagaraj et al. 2023). The working principle of YOLO involves dividing an image into a grid and making predictions on bounding boxes and class probabilities for each grid cell. By employing maximum suppression, the algorithm removes overlapping bounding boxes to provide the final detection results. YOLO offers advantages over alternative object detection algorithms, including its speed, accuracy, and capability to detect objects of sizes and shapes. To enhance its performance and accuracy, further researchers have developed versions of YOLO such as YOLOv3 and YOLOv4; in this study, we use YOLOv8. This powerful tool for object detection finds applications in fields ranging from autonomous driving and medical diagnosis to the fashion industry.

Case-Based Reasoning (CBR), Figure 1 shows the CBR cycle, serves as a versatile AI technique employed for problem solving, reasoning, and learning purposes as decision support component that search and identify similar cases from a database. Its implementation spans domains such as finance, e-learning platforms, medical diagnosis systems, and predictive analytics. The CBR methodology operates similarly to how humans' reason and solve problems, which contributes to its effectiveness. CBR methodology can be applied for diagnosis and decision support. The goal of this paper is to provide a systematic method for detecting bruises in humans using the YOLO algorithm. This method, which uses computer vision techniques, can help improve the accuracy and efficiency of recognizing bruises, leading to better diagnostic outcomes and patient treatment.

## 1.1 Objectives

The objective of this study is to encourage the use of AI in healthcare systems that supports the decision-making process and to contribute to the development of computer-assisted diagnostic procedures using the latest open-source algorithm such as YOLOv8. Furthermore, CBR has already been widely used in several healthcare fields, making it very affordable and easy to integrate into existing systems. In addition, the study focusses on the detection of bruises in visible areas of the body, such as the arms, face, and legs, as provided by a publicly available dataset. It is critical to note that, as a scope, the study does not address the classification of different types of bruises such as contusions, hematoma, and petechiae.

The rest of this paper is organized as follows. Section 2 is the related work reviewing case-based reasoning (CBR) and YOLO in the health care domain. Section 3 proposes the conceptual CBR methodology and YOLO for detecting bruises and Section 4 presents the results and discussion of the findings. The conclusion is presented in Section 5 of this study.

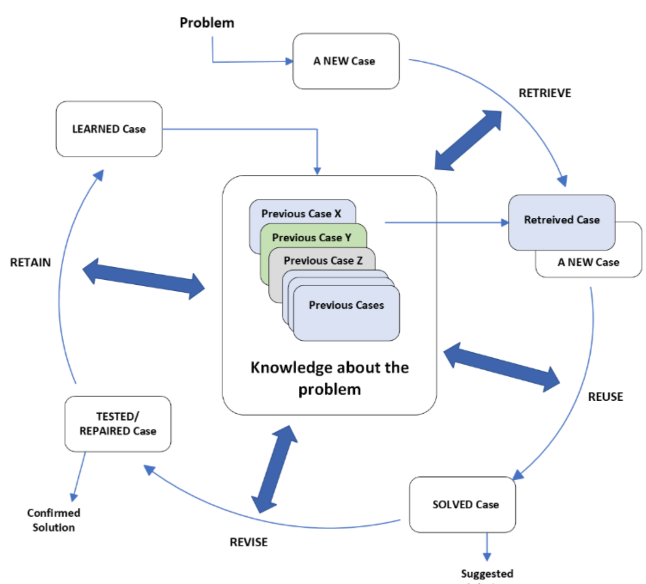


Figure 1. CBR Cycle

## 2. Literature Review

This section reviews the research done on YOLO and CBR in the domain of healthcare systems as well as the detection of bruises. Identifying bruises is a crucial step in diagnosis and medical image analysis, in general. There are many research studies that identify the age of the bruise using sophisticated equipment such as Multispectral Imaging (MSI) (Sprigle et al. 2007) and using visible diffuse reflectance spectroscopy to identify the age of the bruise (McMurdy et al. 2007). In addition, there is a study by (Stam et al. 2010) that uses a 3D model simulation to examine how skin thickness, bruise diameter, and diffusivities impact the healing of bruises. Another study that proves the possibility of infrared-aided photography could be used to identify a prior accidental injury after the skin changes associated with the injury have resolved and are no longer apparent to the naked eye (Rowan et al. 2010).

One of the most challenging and prevalent problems in computer vision is object detection. During the past decade, researchers have been working to develop new methods and techniques that can improve the performance of this challenging task. These include the use of deep models for segmentation, localization, and classification. Due to their fast inferences, YOLOs are commonly used in various applications, such as image recognition. For instance, the detection accuracies of Fast-RCNN and YOLO are around 70 and 63.4, respectively. However, in contrast, the time it takes to perform inference is around 300 times faster with YOLO (Diwan et al. 2023).

YOLO object detections have been used in many application areas in the health care sector that provided solutions for the diagnosis of diseases based on images. A study by (Nie et al. 2019) uses YOLO deep conventional neural network to detect melanoma. Another study by (Rivero-Palacio et al. 2022) used the YOLOv5 algorithm in an embedded mobile application to detect anemia with promising precision for the results. Furthermore, another study by (Aldughayfiq et al. 2023) used YOLOv5-Based learning model for pressure ulcer classification and detection, resulting in better patient outcomes and reduced cost of healthcare. Furthermore, a study by (Tareq et al. 2023) proved that using the hybrid YOLO ensemble and transfer learning model will improve the accessibility of oral healthcare in rural areas with limited resources.

The use of case-based reasoning systems in healthcare has led to the development of effective and efficient diagnostic and treatment procedures for various diseases. It can help with decision support and diagnosis. For example, there is a study (Alexandrini et al. 2003) that investigated the possibility of integrating CBR into health care organizations. They developed a CBR-based system able to retrieve written text of medical documents and convert them into a structured report. A case-based expert system was able to identify a similar case within the Euclidean framework using the k-nearest neighbor algorithm (Chattopadhyay et al. 2013). Another example also is that an illustration prototype called the Swine Flu Diagnostic Assistant (SFDA) has been created using CBR techniques to aid in diagnosing cases of Swine Flu (Chakraborty et al. 2011). An example of a CBR in diabetes management and treatment is presented in an application. The system analyzed patient records such as physical examination and laboratory results. Then it compared these with previous cases using the k-NN algorithm (Kiragu and Waiganjo 2016). A novel TOPSIS-CBR goal programming approach (Malekpoor et al. 2022) was proposed for sustainable healthcare treatment; the proposed method can help oncologists make better decisions regarding the treatment of their patients. It can also deliver a high dose to cancer cells while ensuring that the surrounding organs do not get damaged. The effectiveness of the system is tested by analyzing real data collected from a hospital in Nottingham.

Furthermore, the systems proposed by (Amin et al. 2013) to diagnose and predict diseases are based on the extraction of hidden relationships and patterns from medical records. These methods can be useful in the design of efficient decision support systems.

## 3. Methods

To prepare for the study, images of bruises from different sources, such as medical journals and online databases, were studied and collected to train a decision support system that will automatically detect injuries. The dataset was subsequently exposed to a sequence of steps in order to guarantee that it was fit for machine learning intentions. First, the requirements and objectives of the dataset were identified. Second, the images were collected from different resources to guarantee a uniform and diverse representation of the bruises. This is critical to train a model that can accurately identify injuries. Medical databases, clinical records, personal photos, and research studies were utilized to create the data. Then we labelled the images to ensure that they contained the correct location and details. To train the model, we used the Roboflow annotation tool (Roboflow Universe: Open Source Computer Vision Community) to define frames around the bruises, which allowed to learn about their visual appearance, see 2.

Analyzing and labelling the data accurately is very important to ensure that the system can detect and identify bruises. To ensure that model training and evaluation are performed correctly, we divided the data set into three groups: training, validation, and testing. The training set consisted of 78% of the photos and the validation set included 15% of the images. This allowed us to monitor the performance of YOLOv8. About 7% of the images were used for the test set, which was an independent evaluation of the system's final performance. Prior to the start of the training phase, we utilized various preprocessing techniques to improve the quality of the images and their usability. These included cropping or resizing them to a consistent size and normalizing the values. We also utilized random flipping, rotation, and scaling to increase the data set's diversity and improve its generalizability; augmentation process; see example in Figure 3. Figure 4 shows the image processing cycle using YOLOv8 to generate the initial database and the YOLO model.

Figure 2. Image annotation using Roboflow dataset.

Figure 3. Data Augmentation

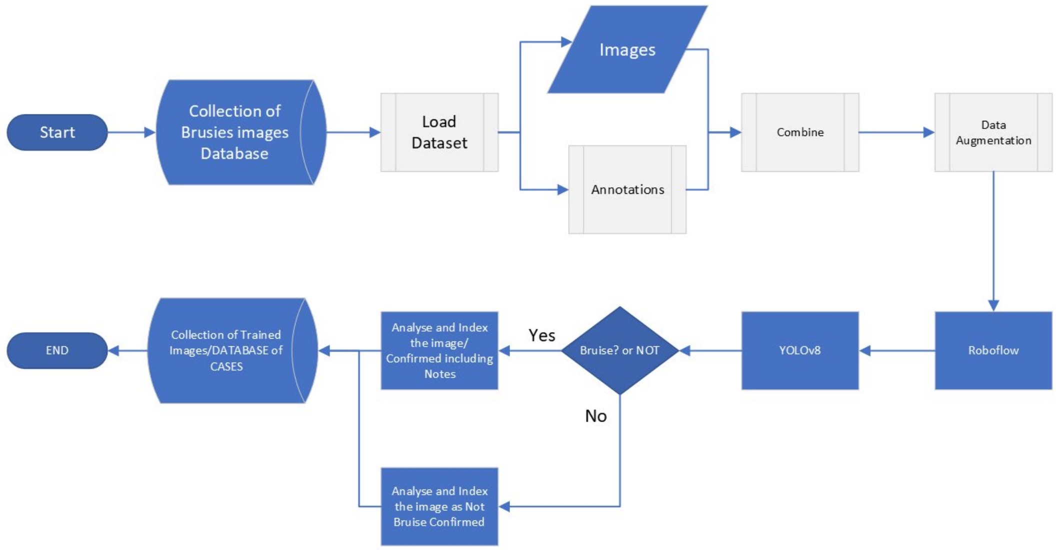


Figure 4. Images processing cycle using YOLOv8.

For the second stage, we integrate the YOLOv8 model that has been trained into the CBR cycle. The goal of this system was to integrate the YOLOv8 object recognition framework for automatic detection of bruises into CBR, and we call it a CBR-YOLO approach and depicted in Figure 5. The three main components of the system are the output, input, and detection modules. So, users can basically upload an image of a bruise to the input module, which will then process the image and send it to the detection section.

The YOLOv8 model is used in the detection module to identify bruises in the image and compare it with a retrieval case. It outputs the coordinates of boxes around the objects detected by the system, as well as labels and confidence scores for each box. The output module provides an interactive and intuitive way for users to learn about the results of the system's automated detection of bruises. It displays the original image with the boxes around the edges highlighted in varying colors, and users can click on the boxes to view their details, such as the location, size, and confidence score of the bruise.

The output module displays the results of the procedure to detect bruises in an interactive manner. It includes the original image with boxes around the edges that are colored differently. The user can then click on the labelled boxes to inspect the details of the bruise, such as its dimensions and location.

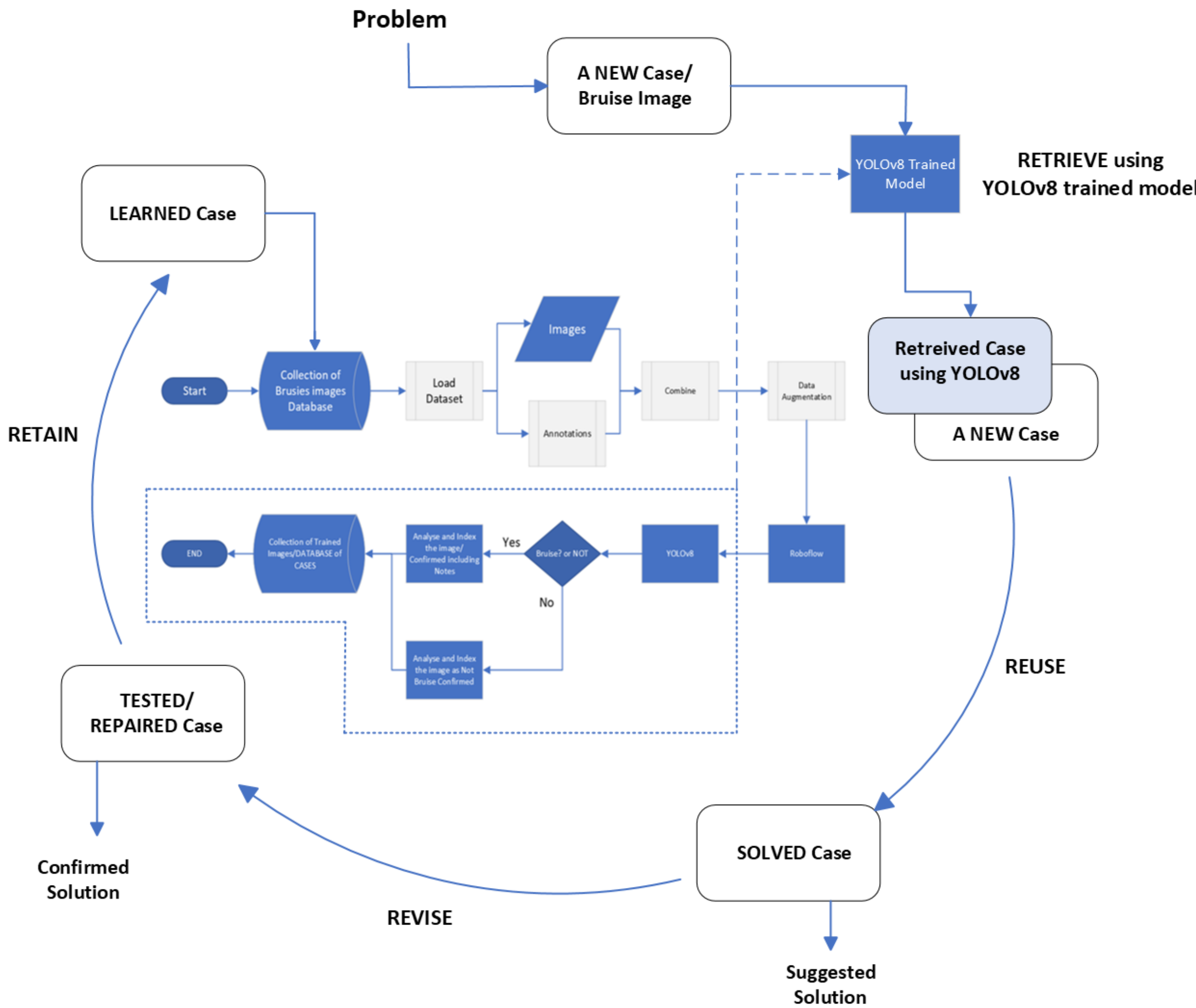


Figure 5. CBR-YOLO proposed model

## 4. Results and Discussion

In this study, several experiments were carried out to validate the accuracy of the models; at least, the bruises were identified. Additionally, we tested YOLOv5, YOLOv7, and YOLOv8. The performance of the latter outweighs those of the previous versions. Google Colab was used to train the CBR-YOLO model object detection framework using GPU. Although this model is capable of running on CPU, it can be improved by utilizing GPU. The results of the proposed integration of CBR and YOLOv8 are promising in terms of instant detection with a high degree of confidence. The CBR-YOLO approach showed a high level of accuracy when it came to properly detecting bruises for the test data group. The model was also able to detect and classify multiple locations of bruises in the same area. This allows it to demarcate the types of bruises, see Figure 6.

The input images in the proposed model were set to 640 × 640 pixels with epochs of 25 and a batch size of 8. The models were trained for 20 training steps to obtain a converged result with the lowest average loss. To further optimize the training parameters, the initial learning rate was set to 0.1while the momentum was set to 0.9. Additionally, a weight decay of 0.005 was used to avoid overfitting of the model. During training, we monitored the loss function, which is a combination of localization and classification losses, to ensure that the model is converging. We used the mean average precision (mAP) metric, which is a standard evaluation metric for object detection, to evaluate the performance of the model in the validation set.

The results of the YOLOv8 show that there is potential for successful outcomes in terms of the rapid diagnosis of bruises without the need for complex equipment. The method can be used as an initial diagnostic tool for photographs of bruises, which can help provide timely and suitable medical treatment. Figure 6 shows the detection of bruises in the test images.


Figure 6. Testing Result Samples

One of the main advantages of using YOLO and CBR for medical image analysis is the ability to provide fast and accurate detection of abnormalities such as bruises, as well as the possibility of generating comments and severity scores and attaching them to the training process for each case. This adds another dimension to the diagnostic process, as it not only identifies the location and type of the abnormality or bruises, but also evaluates its severity and provides relevant instantaneous feedback.

## 5. Conclusion

Integrated Case-Based Reasoning and YOLO have been applied together as an approach to diagnosis and identification of bruises. In this paper, we have proposed the CBR-YOLO approach for the identification of bruises. There is one process that differs from the original case-based framework (YOLO prediction process).

The result of the CBR-YOLO approach is quite significant decision-making for practitioners in the healthcare setting. Especially, it can give suggestions and comments although the bruises are similar in shape. Consequently, the proposed methodology is beneficial for the diagnostic system.

## Acknowledgements

This work was supported by the Interdisciplinary Research Center for Smart Mobility and Logistics, King Fahd University of Petroleum and Minerals, under grant INML2204.

## References

Aldughayfiq, B., Ashfaq, F., Jhanjhi, N.Z. and Humayun, M. YOLO-Based Deep Learning Model for Pressure Ulcer Detection and Classification, *Healthcare*, vol. 11, no. 9, p. 1222, 2023.

Alexandrini, F., Krechel, D., Maximini, K. and von Wangenheim, A. Integrating CBR into the health care organization, in *16th IEEE Symposium Computer-Based Medical Systems, 2003. Proceedings.*, pp. 130–135, 2003.

Amin, S.U., Agarwal, K. and Beg, R. Genetic neural network based data mining in prediction of heart disease using risk factors, in *2013 IEEE Conference on Information & Communication Technologies*, pp. 1227–1231, 2013.

Chakraborty, B., Srinivas, S.I., Sood, P., Nabhi, V. and Ghosh, D. Case Based Reasoning methodology for diagnosis of Swine Flu, in *2011 IEEE GCC Conference and Exhibition (GCC)*, pp. 132–135, 2011.

Chattopadhyay, S., Banerjee, S., Rabhi, F.A. and Acharya, U.R. A Case-Based Reasoning system for complex medical diagnosis, *Expert Systems*, vol. 30, no. 1, pp. 12–20, 2013.

Diwan, T., Anirudh, G. and Tembhurne, J.V. Object detection using YOLO: challenges, architectural successors, datasets and applications, *Multimedia Tools and Applications*, vol. 82, no. 6, pp. 9243–9275, 2023.

Hartley, M., Gounder, P. and Oliphant, H. Spontaneous periocular ecchymosis: a major review, *Orbit*, vol. 42, no. 2, pp. 124–129, 2023.

Jocher, G., Chaurasia, A. and Qiu, J. YOLO by Ultralytics, Available: https://github.com/ultralytics/ultralytics, 2023.

Kiragu, M. and Waiganjo, P. Case based Reasoning for Treatment and Management of Diabetes, *International Journal of Computer Applications*, vol. 145, no. 4, pp. 20–29, 2016.

Malekpoor, H., Mishra, N. and Kumar, S. A novel TOPSIS–CBR goal programming approach to sustainable healthcare treatment, *Annals of Operations Research*, vol. 312, no. 2, pp. 1403–1425, 2022.

McMurdy, J.W., Duffy, S. and Crawford, G.P. Monitoring bruise age using visible diffuse reflectance spectroscopy, in B Chance, RR Alfano, BJ Tromberg, M Tamura, & EM Sevick-Muraca (eds), *Optical Tomography and Spectroscopy of Tissue VII*, SPIE, p. 643426, Available: https://doi.org/10.1117/12.701592, 2007.

Nagaraj, P., Sathish, S., Mathan Kumar, M., Khan, A., Mohiuddin, A. and Syed Haroon, M. Yolo: Human Detection-Based Intelligent Home Automation using IOT, in *2023 International Conference on Computer Communication and Informatics (ICCCI)*, pp. 1–6, 2023.

Nie, Y., Sommella, P., O'Nils, M., Liguori, C. and Lundgren, J. Automatic Detection of Melanoma with Yolo Deep Convolutional Neural Networks, in *2019 E-Health and Bioengineering Conference (EHB)*, pp. 1–4, 2019.

Redmon, J., Divvala, S., Girshick, R. and Farhadi, A. You Only Look Once: Unified, Real-Time Object Detection, Available: http://arxiv.org/abs/1506.02640, 2016.

Rivero-Palacio, M., Alfonso-Morales, W. and Caicedo-Bravo, E. Anemia Detection Using a Full Embedded Mobile Application with YOLO Algorithm, in AD Orjuela-Cañón, JA Lopez, JD Arias-Londoño, & JC Figueroa-García (eds), *Applications of Computational Intelligence*, Communications in Computer and Information Science, Springer International Publishing, Cham, pp. 3–17, 2022.

Roboflow Universe: Open Source Computer Vision Community *Roboflow*, Available: https://universe.roboflow.com/.

Rowan, P., Hill, M., Gresham, G.A., Goodall, E. and Moore, T. The use of infrared aided photography in identification of sites of bruises after evidence of the bruise is absent to the naked eye, *Journal of Forensic and Legal Medicine*, vol. 17, no. 6, pp. 293–297, 2010.

Sprigle, S., Yi, D., Caspall, J., Linden, M., Kong, L. and Duckworth, M. Multispectral image analysis of bruise age, in M Giger & N Karssemeijer (eds), *Medical Imaging 2007: Computer-Aided Diagnosis*, SPIE, p. 65142T, Available: https://doi.org/10.1117/12.709930, 2007.

Stam, B., van Gemert, M.J.C., van Leeuwen, T.G. and Aalders, M.C.G. 3D finite compartment modeling of formation and healing of bruises may identify methods for age determination of bruises, *Medical & Biological Engineering & Computing*, vol. 48, no. 9, pp. 911–921, 2010.

Tareq, A., Faisal, M.I., Islam, M.S., Rafa, N.S., Chowdhury, T., Ahmed, S., Farook, T.H., Mohammed, N. and Dudley, J. Visual Diagnostics of Dental Caries through Deep Learning of Non-Standardised Photographs Using a Hybrid YOLO Ensemble and Transfer Learning Model, *International Journal of Environmental Research and Public Health*, vol. 20, no. 7, p. 5351, 2023.

University, P.N. bruise detector Dataset, *Roboflow Universe*, Available: https://universe.roboflow.com/pukyong-national-university-0wqcb/bruise-detector, 2023.

Watson, I. and Marir, F. Case-based reasoning: A review, *The Knowledge Engineering Review*, vol. 9, no. 4, pp. 327–354, 1994.

## Biography

**Haitham Saleh** is an Assistant Professor at the Industrial and Systems Engineering Department, King Fahd University of Petroleum and Minerals (KFUPM). He received B.S. and M.S. degrees in Industrial and Systems Engineering from KFUPM, Dhahran, Saudi Arabia in 2008 and 2012 respectively, M.S. degree in Industrial Engineering from the University of Illinois at Urbana-Champaign, Urbana, IL, USA in 2016, and a Ph.D. degree in Industrial Engineering from Purdue University, West Lafayette, IN, USA in 2018. His research interests are in the areas of applied optimization/operations research, artificial intelligence, complex systems modeling, and intelligent decision support systems.