ISRES Publishing

The Eurasia Proceedings of Science, Technology, Engineering & Mathematics (EPSTEM)
ISSN: 2602-3199

The Eurasia Proceedings of Science, Technology, Engineering & Mathematics (EPSTEM), 2023

Volume 24, Pages 126-134

IConTech 2023: International Conference on Technology

A Research on Determining the Degree of Risk by Using ResNet

Serap Tepe
The University of Health Sciences

Serkan Eti
Istanbul Medipol University

Abstract: Risk analysis, considered one of the most crucial building blocks of occupational safety with a multidisciplinary approach, is an area that requires quick solutions with proactive methods, has high operational costs, and a low error tolerance level. Utilizing image classification and enabling learning is the main goal of this study to achieve objective outcomes in risk analysis, reduce costs, increase efficiency, and ensure standardization. For the proposed paper, 325 labeled images were collected from the field, standardized to a resolution of 224x224, and a separate file was created for each category after labeling. Python's TensorFlow Keras libraries were used, and the model employed was a semi-learned ResNet model. While 501,765 parameters were learned, 23,587,712 parameters were trained from the data. The total parameter count was 24,089,477. Categorical cross-entropy was used as the loss function, Adam optimization algorithm was preferred for parameter optimization, and the Accuracy Rate metric was used to evaluate the model's quality. The learning success of the model reached 58% in 100 steps, and the maximum accuracy rate observed was determined to be 67%. Traditional risk analysis methods rely on statistical analysis of historical data to obtain results, while machine learning-based approaches allow for the evaluation of complex and multidimensional data. Machine learning-based image classification methods assist in effectively performing risk analysis in situations involving visual information. These techniques make valuable contributions to identifying and managing potential risks in different sectors. As research and applications in this field continue to grow in the future, the role of image classification in risk analysis will gain even more importance.

Keywords: Image processing, Image classification, Risk analysis, ResNet, Occupational safety

Introduction

Image processing is the process of obtaining and analyzing information from digital images using various algorithms and techniques through computers (Gonzalez & Woods, 2008). In this field, properties of images such as color, brightness, and contrast can be modified, edges and corners can be detected, objects can be recognized, and the quality of images can be enhanced. The fundamental purpose of image processing is to render acquired information more meaningful for application in various contexts (Pratt, 2007). The essential components of image processing consist of analog-to-digital converters that transform images into digital format, algorithms that process images, and digital-to-analog converters that transform processed images into visual or numerical outputs (Sonka et al., 2014). These procedural steps are executed using diverse algorithms and methodologies employed in various applications (Jain, 1989).

Image processing plays a significant role in fields such as medicine, security, agriculture, automotive, robotics, entertainment, and many more. Within medical imaging, it aids in the detection and monitoring of diseases by providing support for diagnosis and treatment processes, while in security systems, it contributes to the recognition of individuals and objects through technologies like facial recognition and object detection. Image classification is an increasingly significant field within artificial intelligence and image processing. This process involves assigning a given image to specific categories or classes (Krizhevsky et al., 2012). Classification is commonly accomplished using deep learning and machine learning techniques. At its core, image classification encompasses the computer's understanding of images and its ability to identify objects, patterns, or features similar to the human eye (Simonyan & Zisserman, 2014). Presently, deep learning models, particularly Convolutional Neural Networks (CNNs), have achieved substantial success in this domain. Thanks to their multi-layered architectures, these models learn features hierarchically from images, thereby enhancing accuracy and performance (He et al., 2016).

Risk is a concept stemming from the combination of probability and severity. Probability encompasses situations that have a likelihood of occurrence, while severity refers to the effects that will emerge based on the outcomes of these situations. Risk essentially constitutes a fusion of the infinite possibilities of probabilities and the traces left when any of these possibilities materialize. From this perspective, risk is thought to possess a complex structure with both pre- and post-components.

In the pre-component stage, which is referred to as the "before" phase, managing probabilities and taking proactive measures are necessary. This phase involves activities aimed at controlling the potential risks of events, places, individuals, and situations. The post-component stage, labeled as the "after" phase, includes activities required to minimize the damage resulting from realized risks and to navigate through them with the least possible loss.

Risk is commonly perceived as a threat; however, it is actually also associated with opportunities. Risk analysis constitutes a set of methods used to identify, mitigate, and reduce hazards to an acceptable level, and each risk analysis holds importance in terms of recognizing available or assessable opportunities. Therefore, through accurate definition and effective management processes facilitated by risk analyses, the transformation of risks into opportunities is plausible. Risk analysis processes can enhance working environments, elevate individual awareness, and unearth possibilities for intervention. By precisely identifying and efficiently managing risks, not only can the current state be maintained, but there is also a chance to elevate it to a superior level.

In this study, the aim is to achieve real-time detection of risk analyses, a crucial field in occupational safety, through the assistance of image classification, with the objective of eliminating subjectivity in classification. The motivation behind the study lies in the prevention of negative or inadequate situations arising from subjective assessments in risk analysis within occupational safety. It strives to enable swift and effective decision-making through instant detection, prompt intervention, proactive approaches, increased efficiency, and reduced operational costs. In this context, the subsequent sections of the study are organized as follows.

The second section of the study provides a literature review, delving into the topics of image processing, image classification, and risk analysis. The third section succinctly summarizes the methodology of the study. The fourth section presents the findings, and the following sections discuss the acquired findings, culminating in the evaluation of the results.

Literature Review

In parallel with scientific and technological advancements, computer technology has been applied to various fields, offering numerous conveniences (Fradi et al., 2022). One of these areas is the widely acclaimed field of image processing (Sotvoldiev et al., 2020). Image processing involves the manipulation of image data using various algorithms or mathematical methods in a computer environment. Fundamentally, it revolves around capturing digital images, digitizing them into the desired format, conducting analyses, and ultimately transforming the image into desired parameters to obtain the final output (Soyhan et al., 2021; Venkatakrishnan & Kalyani, 2016; Zhang, 2022). To process images digitally, the first step is to create and transfer data libraries into a digital environment. Once these data libraries are established, the images are processed, and the procedure is carried out (Sin & Kadıoglu, 2019).

Image processing methods enable rapid and efficient error detection processes, allowing for comprehensive product differentiation and classification within very short timeframes. Additionally, image processing methods minimize issues such as human exposure to risky environments in terms of health and safety. The advancing computer control systems, automatic machine systems, and cameras contribute to faster, safer, and more accurate operations (Ak & Dereli, 2021; Boyacıgil, 2022). Due to its capability to significantly enhance performance and efficiency, image processing technology finds extensive applications across various domains like military, medical, and industrial sectors (Feng, 2022). In this context, image processing technology is widely used in areas such as identifying the origin of a chemical through microplate reading tests, automatic counting of items on a factory conveyor belt, detecting cracks in metal welding, cancer detection, remote sensing, and robotic navigation to avoid collisions (Venkatakrishnan & Kalyani, 2016).

There are various techniques used for automatically analyzing images, and the combination of these techniques with image processing technology leads to the emergence of diverse application areas. These techniques encompass 2D and 3D object recognition, image segmentation, motion detection, video surveillance, optical flow, medical scanning analysis, 3D pose estimation, and automatic license plate recognition (Venkatakrishnan & Kalyani, 2016). Image processing is utilized for real-time detection and monitoring of field objects to establish security conditions (Kim et al., 2014). Object recognition, in particular, is a widely employed image processing technology. YOLO algorithms are commonly used for object detection purposes, as indicated by the literature.

In the context of Occupational Health and Safety (OHS), image processing technologies predominantly focus on Personal Protective Equipment (PPE). Basaran and Cagıl (2022) utilized the YOLOv4 algorithm in their study for detecting OHS measures. They designed a system that employs object detection algorithms to monitor the use of protective eyewear. This system facilitates easy monitoring of protective measures in areas where OHS measures are mandatory. Images of eyewear taken through cameras were identified using image processing and deep learning techniques.

Bo et al. (2019) employed the YOLOv3 model for object detection to determine whether construction workers were wearing helmets on construction sites. Torres et al. (2021) developed two different deep learning-based approaches to detect the usage of PPE by workers. Similarly, a real-time object recognition model was developed using data collected from construction sites to detect the use of PPE by workers (Moohialdin et al., 2021). A framework was designed to detect PPE usage in construction workers based on visuals, enabling real-time understanding of whether construction workers adhere to safety rules (Delhi et al., 2020).

Onal and Dandıl (2021) employed the YOLOv4 deep learning algorithm to detect whether workers in industrial production facilities were using appropriate equipment correctly within their working environments. These studies collectively showcase the utilization of image processing and deep learning techniques for enhancing safety measures, monitoring PPE usage, and ensuring compliance with safety regulations across various industries. In their study, Lee and Lee (2023) have developed a CCTV-based security management application using image recognition models. A deep learning-based object recognition model was created by collecting data from images of construction site workers. In the three models they created: firstly, the aim was to check whether construction workers are present at the construction sites and to identify unauthorized entries into the work area; in the second model, the goal was to detect workers' postures to identify falls, predict hazardous situations in advance, and thereby intervene in case of an accident as quickly as possible; the third model was used to determine whether employees are wearing their PPEs (Personal Protective Equipment) such as helmets.

Ahn et al. (2023), on the other hand, designed a visual monitoring system named SafeFac to detect human activities near assembly lines in a factory, aiming to prevent injuries to workers due to accidents. This system utilizes a deep learning model based on YOLOv3 and supports multiple camera input streams to detect abnormal behaviors occurring near machinery. Although most of the modern factory operations are automated, unexpected accidents are still possible. In a similar vein, Yu et al. (2017) developed an image-based method to detect unsafe behaviors of construction workers in real-time. On the other hand, with the support of artificial intelligence, image processing technology has given rise to various applications in the field of Occupational Health and Safety (OHS) as highlighted by Turker et al. (2023). Through AI applications, it is expected that risks present in workplaces can be analyzed, proactive preventive measures can be identified, accident data can be analyzed, and work-related accidents and occupational diseases can be prevented (Fu et al., 2020).

Current camera images can be processed using AI algorithms to enable data analysis and real-time video content analysis. Smart manufacturing and intelligent security systems allow for the monitoring of risky activities that could lead to injuries, and through data obtained from wearable devices, swift actions can be taken in case of potential accidents (Shiklo, 2018). The intelligent security system developed by Erkan et al. (2015) processes images captured by cameras and activates an alarm and sends an email to the relevant unit in case of a threat. The system can be controlled remotely, and during the scanning process, information about the object's height and width can be accessed. Balakreshnan et al. (2020) combined Microsoft Azure image technology with AI to develop a system that determines whether protective goggles are worn in a factory setting. The combination of Unmanned Aerial Vehicles (UAVs), also known as drones, and image processing methods makes it inevitable for UAVs to enter various domains of our lives (Sin and Kadıoglu, 2019). For instance, through UAVs, engineering of risk assessment and management procedures becomes possible (Salvini et al., 2017).

In their study, Rossi et al. (2016) designed a UAV capable of detecting gas leaks. The UAV system, equipped with a gas measurement sensor and a 4G communication module, slows down its speed during autonomous flight when gas concentration increases, transmitting coordinate and gas measurement information to the control system through the 4G communication module. Asad et al. (2017) created a system capable of detecting concentrations of CO, CO2, and H2S gases using gas sensors, thermal cameras, and Cyber-Physical Systems (CPS) data. The data was integrated using a point density algorithm in the ArcGIS Pro computer software.

Image classification is a machine learning technique aimed at categorizing images into specific classes (Liu et al., 2016). Image classification involves predicting a label for an input image based on its visual content (Rajalingappaa et al., 2015). The objective is to assign a class label to an input image based on predefined categories. This learning approach falls within the realm of supervised learning (Yao & Fei-Fei, 2010), where a model is trained on a labeled dataset. The quality of such a model is evaluated on a separate test dataset. The architecture and training process of the model play a crucial role in achieving high accuracy in image classification tasks (Krizhevsky et al., 2012). This technique finds diverse applications across various domains.

Image classification is employed in e-commerce to categorize product images, organize search results, and determine product categories. In medical image analysis, it is utilized for classifying medical images like X-rays and MRIs to aid in disease diagnosis. In content filtering, image classification serves to filter and protect against inappropriate content. Additionally, image classification is used for driverless vehicles to classify traffic signs and road images, enabling vehicles to navigate and comprehend their surroundings. Within the realm of visual media, it facilitates the classification and tagging of photographs and videos (Goodfellow et al., 2016, Minaee et al., 2020; Ren et al., 2015; He et al., 2016; Redmon et al., 2016). These applications underscore the significance and wide-ranging utility of image classification. Irrespective of the method, the ultimate goal of all developed image processing and classification techniques is to minimize hazards and risks in the working environment within the Occupational Health and Safety (OHS) domain, and to enhance the efficiency and speed of monitoring processes. Through these developed systems, the aim is to mitigate the impact on workers and the workspace in the event of an accident, and thus reduce the potential workload and losses that might arise in such scenarios.

Method

The Convolutional Neural Network (CNN) is a widely used deep learning algorithm in image classification tasks. CNNs are a type of deep neural network and are commonly employed in computer vision tasks, particularly in image classification. They are designed to process grid-structured data with interactive pixels such as images, videos, and audio signals. CNNs are tailored to handle grid-structured data with interactive pixels like images. In a CNN, the first layer serves as the input layer and helps extract local features from the image. Subsequent layers are built to construct higher-level, more abstract features. The final layer is designed to extract class scores and make predictions as the outcome.

A distinctive feature of CNNs is the use of convolutional layers that apply filters to input data. The pooling layer aims to subsample the output of the convolutional layer and reduce its dimensions. This allows the model to detect significant features and learn unique representations of the data, enabling CNNs to be effective in image classification tasks. In CNNs, an input image undergoes several layers of convolutional and pooling operations, with each layer learning more complex features. The convolutional layer applies filters to the input image, which are used to extract local features. These filters are learned during the training process and capture relevant patterns in the image. Subsequently, the pooling layer reduces the spatial dimensions of the output from the convolutional layer. This makes the model computationally efficient and prevents overfitting by preventing the memorization of training data. In other words, it prevents excessive learning. After several layers of convolutional and pooling operations, the final layer of the CNN generates a probability distribution over defined class. The class with the highest probability is selected as the final prediction.

The utilization of convolutional layers and pooling operations makes CNNs particularly effective for image classification tasks. The convolutional layer enables the model to learn local features like edges and textures, and more complex features are learned in subsequent layers. The pooling layer further enhances the model's unique response to small translations and changes in the input image, making it more resilient to variations in the data.

Residual Network (ResNet) is a type of neural network used in deep learning. It was developed by Microsoft Research in 2015 to improve the structure of very deep neural networks. ResNet addresses the vanishing gradient problem in earlier layers of deep networks, preventing overfitting and structural loss. ResNet uses a function called a skip connection or shortcut connection. This function combines the input of a layer with its output, preventing overfitting. The skip connection also facilitates the updating of data and preserves features from previous layers. Due to its ability to prevent overfitting and enhance the structure of deep networks, ResNet is widely used in various visual applications like image classification, object recognition, and face recognition. ResNet has produced top results in numerous image classification benchmarks and has played a pioneering role in deep learning research.

In the mentioned study, the aim was to classify images obtained for occupational safety according to their risk levels. Towards this goal, the ResNet algorithm was implemented using Python for training the model. To achieve this objective, a total of 325 images captured at different times from the field were utilized for training the established model. These images were labeled through expert assessment. The labeling process involved the use of 5 categories. The first category represents images with the lowest level of risk, while the fifth category includes images of the most hazardous areas. The distribution of categories in the training dataset is provided in Table 1 and Figure 1.

Table 1. The distribution of categories

The number of images in Category 1	45
The number of images in Category 2	49
The number of images in Category 3	79
The number of images in Category 4	68
The number of images in Category 5	84

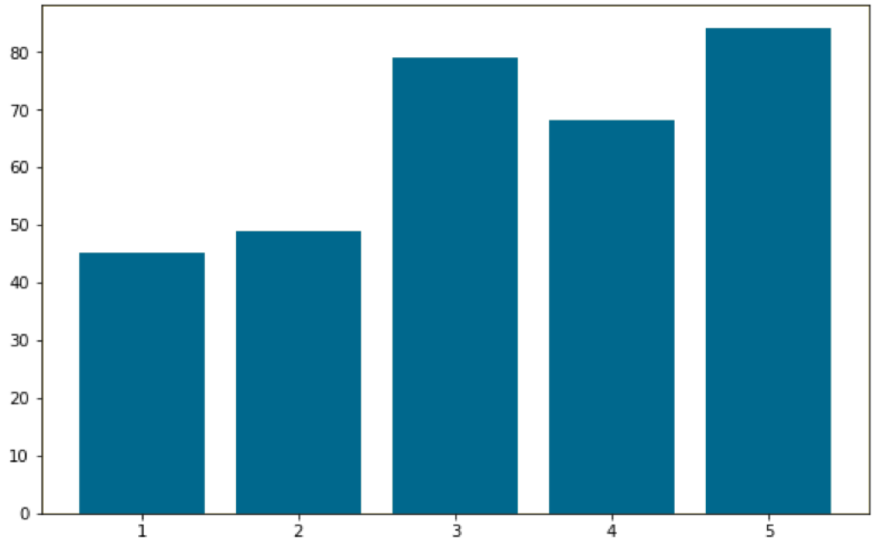

Figure 1. The distribution of categories

Findings

In the proposed study, after labeling, all images were standardized and resized to a resolution of 224x224. A file was created for each category. The TensorFlow Keras library in Python was utilized for this purpose. Upon examining the model, a pretrained ResNet model was employed. While 501,765 parameters were learned, the model was trained to learn 23,587,712 parameters from the data. The total number of parameters is 24,089,477. The categorical cross-entropy loss function was used, and the Adam optimization algorithm was chosen for parameter optimization. The Accuracy Rate metric was utilized to assess the quality of the model. Throughout the learning process of the model, with 100 epochs and a batch size of 16, the variation of the loss value and accuracy value is depicted in Figure 2 and Figure 3.

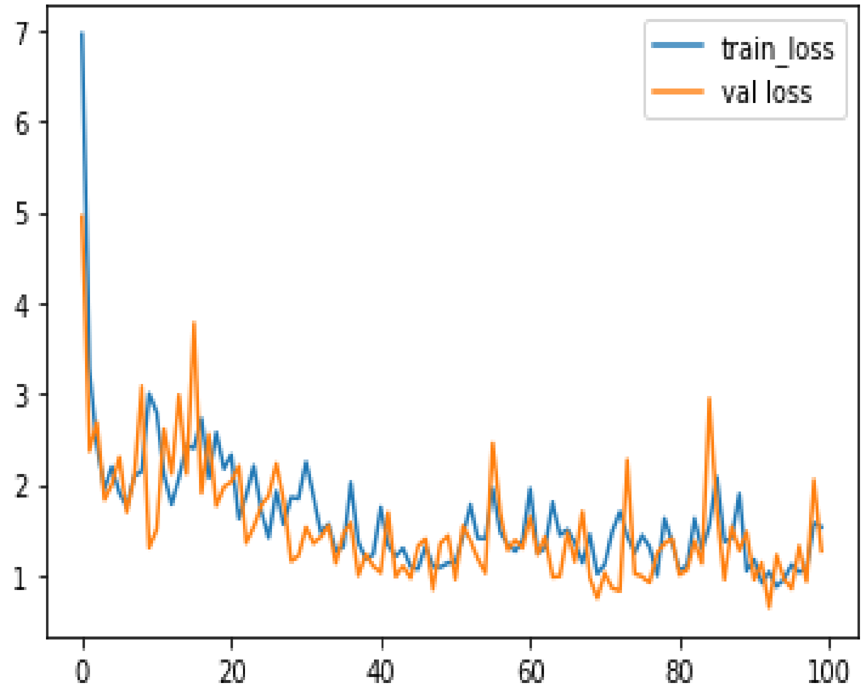

Figure 2. Loss value

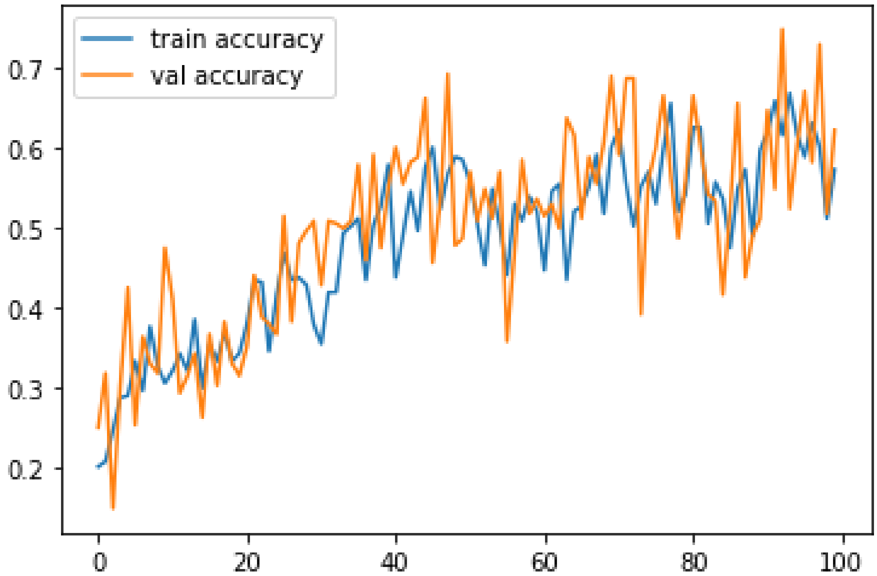

Figure 3. The rate of change of the accuracy value

The learning success of the model reaches 58% accuracy in 100 steps, with its peak value being 67% accuracy. In other words, the accuracy of correctly labeling a given image is observed to be around 60%. This rate, which could be considered high for a five-category model, can be further improved with more data to enhance its learning.

Results and Discussion

Risk analysis in occupational safety is a crucial process aimed at identifying, assessing, and preventing potential hazards in workplaces. In this process, risk analysis is used to identify potential hazards in workplaces and evaluate the risks these hazards may pose, making it an effective method as well as a legal requirement. In risk analysis, accurate and rapid analysis of data holds critical importance in obtaining accurate results.

In this context, image classification methods play a significant role in occupational safety risk analysis. Image classification relies on analyzing visual data to detect hazardous situations, potential risks, and security breaches in workplaces. Occupational safety experts can utilize images obtained from security cameras to identify hazardous situations and anticipate potential risks, contributing to proactive safety measures.

Image classification methods, powered by deep learning and artificial intelligence algorithms, can operate with high accuracy and sensitivity. This technology aids in swiftly detecting hazardous situations and can mitigate risks arising from human errors. Moreover, it enables occupational safety experts to redirect their time and efforts towards other vital tasks. As a result, image classification techniques have the potential to revolutionize occupational safety risk analysis by enhancing hazard detection, reducing human-related risks, and optimizing the allocation of expertise and resources.

In this study, for the purpose of conducting risk analysis, a model was established according to the objective. To train the model, 325 images taken at different times from the field were used. These images were labeled through expert evaluations. The labeling involved 5 categories, where the first category represents images with the lowest risk and the fifth category contains images from the most high-risk areas. The model's learning success reached 58% accuracy in 100 steps, with the maximum value observed being 67% accuracy. In other words, the accuracy of correctly labeling a given image is seen to be in the range of 60%. While this rate can be considered high for a five-category model, it can be further strengthened with the assistance of more data.

In conclusion, image classification techniques are a significant tool that enhances the effectiveness of occupational safety risk analysis. They allow for a better understanding of potential hazards and reinforce security measures in workplaces. The integration of innovative technologies into occupational safety practices plays a vital role in preserving the health and safety of workers. Occupational safety is a multidisciplinary field with various stakeholders, and one of the most critical areas of focus is conducting risk analyses. Conventional methods involve risk analyses conducted by occupational safety experts of varying experience levels. Due to differences in experience, age, gender, years of work, and field specialization, disparities can arise in risk assessments, often leading to flawed or inadequate analyses. The study's starting point addresses the prevention of negative or insufficient situations resulting from person-dependent evaluations during risk analysis in occupational safety. The aim is to achieve rapid and effective decision-making through instant detections, swift interventions, proactive approaches, increased efficiency, and reduced operational costs. The method utilized in this study yields accurate results, with a success rate of up to 60% in correctly labeling images, aligning with these objectives. In future studies, it is anticipated that the method's enhancement, expansion of application areas, and diversification of work environments will lead to even more successful outcomes.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Acknowledgements or Notes

* This article was presented as an oral presentation at the International Conference on Technology (www.icontechno.net) held in Antalya/Turkey on November 16-19, 2023.

References

Ahn, J., Park, J. Lee, S.S., Lee, K., Do, H. & Ko, J. (2023). Safefac: Video-based smart safety monitoring for preventing industrial work accidents. *Expert Systems with Applications, 215.*

Ak, Y. & Dereli, S. (2021). Bir otomasyon hattında parca secim ve ayrıstırma islemlerinde kullanılan coklu robotlar icin goruntu isleme temelli gorev ataması yapan sistem onerisi. *ISITES2021,* 82-90. Sakarya, Turkey.

Asad, M., Aidaros, O.A., Beg, R., Dhahri, M. A., Neyadi, S. A., & Hussein, M. (2017). Development of autonomous drone for gas sensing application. *2017 International Conference on Electrical and Computing Technologies and Applications (ICECTA)*, 1-6.

Balakreshnan, B., Richards, G., Nanda, G., Mao, H., Athinarayanan, R., & Zaccaria, J. (2020). PPE compliance detection using artificial intelligence in learning factories. *Procedia Manuf., 45,* 277–282.

Basaran, G., & Cagıl, G. (2022). Koruyucu gozluk kullanımının goruntu isleme yontemiyle tespit edilmesi. *El-Cezeri, 9*(1), 86-95.

Bo, Y., Huan, Q., Huan, X., Rong, Z., Hongbin, L., Kebin, M., ... & Lei, Z. (2019). Helmet detection under the power construction scene based on image analysis. In *2019 IEEE 7th international conference on computer science and network technology (ICCSNT),* 67-71. Dalian, China.

Boyacıgil, M.F. (2022). *Goruntu isleme teknikleriyle bir endustriyel kalite kontrol uygulaması*. (Master's dissertation). Necmettin Erbakan University, Konya.

Delhi, V.S.K., Sankarlal, R., & Thomas, A. (2020). Detection of personal protective equipment (PPE) compliance on construction site using computer vision based deep learning techniques. *Front. Built Environment, 6*, 136.

Erkan, E., Ozcalık, H.R. & Yılmaz, S. (2015). Goruntu isleme teknikleri kullanılarak insan hareketlerini algılayan akıllı guvenlik sistemi tasarımı. *Journal of Engineering and Science*, *3*(1), 1-6.

Feng, L. (2022). Application analysis of artificial intelligence algorithms in image processing. *Mathematical Problems in Engineering,* 10.

Fradi, M. Zahzah, E. H. & Machhout, M. (2022). Real-time application based CNN architecture for automatic USCT bone image segmentation. *Biomedical Signal Processing and Control*, *71*.

Fu, G., Xie, X., Jia, Q., Li, Z., Chen, S., & Ge, Y. (2020). The development history of accident causationmodels in the past 100 years: 24Model, a more modern accident causation model. *Process Safety and Environmental Protection, 134,* 47-82.

Gonzalez, R. C., & Woods, R. E. (2008). *Digital image processing.* Pearson Education.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning* (Vol. 1). *MIT Press.*

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of *the IEEE conference on computer vision and pattern recognition* (CVPR) (pp. 770-778*).*

Jain, A. K. *(1989). Fundamentals of digital image processing.* Prentice Hall.

Kim, H., Elhamim, B., Jeong, H., Kim, C., & Kim, H. (2014). On-site safety management using image processing and fuzzy inference. *International Conference on Computing in Civil and Building Engineering,* 1013-1020.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems (NIPS)*, 1097-1105.

Lee, J. & Lee, S. (2023). Construction site safety management: A computer vision and deep learning approach. *Sensors*, *23*(2), 944.

Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C. Y., & Berg, A. C. (2016). SSD: Single shot multibox detector. In *European Conference on Computer Vision* (pp. 21-37). Springer.

Minaee, S., Boykov, Y., Porikli, F., & Plaza, A. J. (2020). Image segmentation using deep learning: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence.*

Moohialdin, A., Lamari, F., Marc, M., & Trigunarsyah, B. (2021). A real-time computer vision system for workers PPE and posture detection in actual construction site environment, *EASEC16* (pp.2169-218). Springer: Singapore.

Onal, O., & Dandıl, E. (2021). Object detection for safe working environments using YOLOv4 deep learning model. *Avrupa Bilim ve Teknoloji Dergisi*, *26,* 343-351.

Pratt, W. K. (2007). *Digital image processing.* John Wiley & Sons.

Rajalingappaa, M., Niblack, W., Stober, J., & Nguyen, T. (2015). A deep learning based approach for automatic fetal facial feature detection and recognition. In *International Workshop on Machine Learning in Medical Imaging* (pp. 62-70*).* Springer.

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 779-788).

Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards real-time object detection with region proposal networks. *In Advances in Neural Information Processing Systems (NIPS 2015),* 91-99

Rossi, M. & Brunelli, D. (2016). Autonomous gas detection and mapping with unmanned aerial vehicles. *IEEE Transactıons on Instrumentation and Measurement, 65*(4), 1-11.

Salvini, R., Mastrorocco, G., Esposito, G., Bartolo, S., Coggan, J. & Vanneschi, C. (2017). Use of a remotely piloted aircraft system for hazard assessment in a rocky mining area Lucca, Italy. *National Hazards and Earth System Sciences, 18,* 287-302.

Shiklo, B. (2018, December 25). IoT in manufacturing: The ultimate guide. *ScienceSoft.* Retrieved from https://www.scnsoft.com

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *ICLR 2015*.

Sonka, M., Hlavac, V., & Boyle, R. (2014). *Image processing, analysis, and machine vision*. Cengage Learning Inc.

Sotvoldiev, D., Muhamediyeva, T. & Juraev, Z. (2020). Deep learning neural networks in fuzzy modeling," *Journal of Physics: Conference Series*, *144*(1).

Soyhan, I., Gurel, S. & Tekin, S. A. (2021). Yapay zeka tabanlı goruntu ısleme tekniklerinin insansız hava aracları uzerinde uygulamaları. *Europan Journal of Science and Technology, 24*, 469-473.

Sin, B., & Kadıoglu, I. (2019). Insansız hava aracı (IHA) ve goruntu ısleme teknikleri kullanılarak yabancı ot tespitinin yapılması. *Turkish Journal of Weed Science, 22*(2), 211-217.

Tepe, S. (2023). *Saglık sektorunde ıs saglıgı ve guvenligi.* Akademisyen yayınevi.

Torres, P., Davys, A., Silva, T., Silva, L. J. S., Kuramoto, A., Itagyba, B., ... Lopes, H. (2021). A robust real-time component for personal protective equipment detection in an industrial setting (pp.693-700). *Intenational Conference on Enterpise Information Systems, Online Streaming -ICEIS 2021*.

Turker, O., Toprak, O., Erarslan, B.A., Asılıoglu, E., Yılmaz, Y.,…… Engin, N. (2023). *Goruntu isleme teknolojileri. Tasarımda fotograf kullanımı* (1st ed., pp.193-213). Erzurum: *Ataturk Universitesi Acık ve Uzaktan Ogretim Fakultesi Yayını.*

Venkatakrishna, S., & Kalyani, C. (2016). Basic of image processing techonologies. *International Journal of World Research, 1*(34).

Yao, B., & Fei Fei, L. (2010*). Grouplet: A structured image representation for recognizing human and object interactions. Computer vision–ECCV 2010* (pp. 339-352). Berlin, Heidelberg: Springer.

Yu, Y., Guo, H., Ding, Q., Li, H., & Skitmore, M. (2017). An experimental study of real-time identification of construction workers' unsafe behaviors, *Autom. Constr, 82*, 193–206,.

Zhang, X. (2022). Application of artificial intelligence recognition technology in digital image processing. *Wireless Communications and Mobile Computing,*10.

Author Information

Serap Tepe
The University of Health Sciences
Department of Occupational Health and Safety,
Istanbul, Turkey
Contact e-mail: *serap.tepe@sbu.edu.tr*

Serkan Eti
Istanbul Medipol University
Department of Computer Programming, Medipol University
Istanbul, Turkey

To cite this article:

Tepe, S., & Eti, S. (2023). A research on determining the degree of risk by using ResNet. *The Eurasia Proceedings of Science, Technology, Engineering & Mathematics (EPSTEM), 24*, 126-134.