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Evaluation of the Effectiveness of Deep Learning Model in Detection and Classification of Pressure Injury

Basınç Yaralanmasının Tespit ve Sınıflandırılmasında Derin Öğrenme Modelinin Etkinliğinin Değerlendirilmesi

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Abstract

Objective: The study was conducted to determine the effect of the deep learning model on the knowledge and satisfaction levels of nurses in the detection and classification of pressure injuries.

Method: The population of this randomized controlled trial consisted of nurses working in intensive care, internal medicine, and surgical clinics at a foundation university hospital between March and April 2022 who voluntarily participated in the study. The sample consisted of a total of 60 (30 experimental and 30 control) nurses who met the sample criteria. The research data were collected using the Structured Nurse Introduction Form, Modified Pieper Pressure Injury Knowledge Test and Nurse Satisfaction Scale.The research data were analyzed in the SPSS 25.0 program.

Results: The mean age of the nurses in the experimental group was determined as 25.67±7.27, and the control group as 25.10±3.47. 50% of the nurses in the experimental and control groups graduated from health vocational high schools, and 40% of them worked in surgical services. When the nurses' post-training knowledge exam (post-test) scores were compared; the mean score of the experimental group was determined as 39.36±1.88 and the control group as 33.30±1.68. The post-training knowledge level of the experimental group was found to be statistically significantly higher than the control group ($P<.05$). When the success of the pressure injury risk assessment and stage determination was examined, it was determined that the experimental group was able to assess the risk with 97% success with the deep learning model and determine the wound stage with 89% prediction verification. It was determined that the control group determined the patients' risk levels with the Braden pressure injury risk assessment scale at a moderate level with 13.83±4.67 and were 50% successful in stage estimation. The evaluation and stage estimation levels were found to be statistically significantly higher than the control group ($P<.05$). When the satisfaction levels of the nurses participating in the study with the applied training were examined; the average score of the experimental group was determined as 24.60±0.96 and the control group as 20.93±0.63. The satisfaction level of the experimental group with the training was found to be statistically significantly higher than the control group ($P<.05$).

Conclusion: It was determined that pressure injury detection and classification with artificial intelligence technology was more successful than the traditional method.

Keywords: Artificial intelligence, deep learning, pressure injury.

Öz
Amaç: Araştırma basınç yaralanmalarının tespit ve sınıflandırılmasında derin öğrenme modelinin hemşirelerin bilgi ve memnuniyet düzeylerine etkisini belirlemek amacıyla yürütüldü.
Yöntem: Randomize kontrollü tasarımla yürütülen bu çalışmanın evrenini bir vakıf üniversitesi hastanesinde Mart–Nisan 2022 tarihlerinde yoğun bakım, dahiliye ve cerrahi kliniklerde çalışan ve çalışmaya gönüllü hemşireler oluşturdu. Örneklemi ise örneklem kriterlerine uyan toplam 60 (30 deney ve 30 kontrol) hemşire oluşturdu. Araştırma verileri, Yapılandırılmış Hemşire Tanıtım Formu, Modifiye Pieper Basınç Yarası Bilgi Testi ve Hemşire Memnuniyet Skalası kullanılarak toplandı. Araştırma verileri SPSS 25.0 programında analiz edildi.
Bulgular: Deney grubu hemşirelerin yaş ortalaması 25,67±7,27, kontrol grubu 25,10±3,47 olarak tespit edildi. Deney ve kontrol grubu hemşirelerin %50'si sağlık meslek lisesi mezunu, %40'ı cerrahi servislerde çalışmaktadır. Hemşirelerin eğitim sonrası bilgi sınavı (sontest) puanları karşılaştırıldığında; deney grubunun ortalama puanı 39,36±1,88, kontrol grubunun 33,30±1,68 olarak belirlendi. Deney grubunun eğitim sonrası bilgi düzeyi kontrol grubundan istatistiksel olarak anlamlı derecede yüksek bulundu (*P*<,05). Basınç yaralanması risk değerlendirme ve evre tespit etme başarısı incelendiğinde deney grubunun derin öğrenme modeliyle %97 başarıyla risk değerlendirebildiği ve %89 tahmin doğrulamayla yara evresi belirleyebildiği tespit edildi. Kontrol grubunun Braden bası yarası risk değerlendirme ölçeği ile hastaların risk düzeylerini 13,83±4,67 ile orta düzeyde belirlediği saptandı. Deney grubunun basınç yarası risk değerlendirme ve evre tahmin etme düzeyleri kontrol grubundan istatistiksel olarak anlamlı derecede yüksek bulundu (*P*<,05). Araştırmaya katılan hemşirelerin uygulanan eğitimden memnuniyet düzeyleri incelendiğinde; deney grubunun puan ortalaması 24,60±0,96 ve kontrol grubunun 20,93±0,63 olarak belirlendi. Deney grubunun eğitimden memnuniyet düzeyi kontrol grubundan istatistiksel olarak anlamlı derecede yüksek bulundu (*P*<,05).
Sonuç: Yapay zeka teknolojisiyle basınç yaralanması tespit ve sınıflandırmasının geleneksel yönteme göre daha başarılı olduğu tespit edildi.
Anahtar Kelimeler: Basınç yaralanması, derin öğrenme, yapay zeka

INTRODUCTION

Pressure injuries are localized tissue damage that usually occurs on bony prominences and occurs as a result of pressure or shearing forces accompanying pressure. These injuries, which indicate the quality of healthcare services, threaten patient safety, prolong hospital stays, and increase care costs.[1–3] This health problem, which reduces the quality of life of the patient and his/her family, leads to social isolation and requires more nursing care. When adequate care and treatment are not received, it can result in mortality, morbidity and nosocomial infections.[4–7]

Systematic identification and staging of pressure injuries enhance the effectiveness of treatment and positively influence patient recovery. Accurate classification of these injuries improves patient care outcomes and fosters a common language among nurses, thereby increasing the quality of care.[8–11]

It is crucial to utilize innovations and technological advancements to deliver systematic and high-quality nursing care.[11,12] With the rapid advancement of technology, information systems and artificial intelligence applications have begun to be integrated into nursing practices.[12] The concept of artificial intelligence was first defined by John McCarthy as "the science and engineering of making intelligent machines, especially intelligent computer programs." Through AI, systems can be developed that mimic human behavior and model cognitive processes specific to a given field.[13,14]

Medical expert systems, designed to solve problems in the healthcare field, represent one of the most common applications of artificial intelligence. These systems are structured based on the knowledge, experience, and recommendations of medical professionals, allowing for low-error solutions.[13-16] The goal of medical expert systems is not to replace doctors and nurses but to support them by offering decision-making assistance and recommendations based on accurate health data, thereby easing their workload and enhancing care quality.[17–19]

Deep learning, one of the most commonly used branches of medical artificial intelligence, is a new generation machine learning technique that demonstrates high effectiveness in fields such as object recognition, image processing, speech analysis, and natural language processing through multi-layered artificial neural networks. The key distinction between deep learning and traditional machine learning lies in its ability to automatically learn from symbolic representations of data such as images, videos, audio, and text rather than relying on pre-coded rules.[20–22]

The literature includes the use of artificial intelligence and deep learning models for risk analysis of pressure injuries.[22,23] However, no studies have been identified in our country specifically addressing the classification of these injuries. Although these innovative approaches are present and applied in international research, their implementation remains limited within our national context.[24] Based on this background, the present study was conducted to develop a deep learning model for the detection and staging of pressure injuries and to evaluate its impact on nurses' knowledge levels and satisfaction.

Hypotheses;

H1: The mobile application developed using a deep learning model is more effective than conventional methods in enhancing nurses' knowledge about pressure injurs.

H2: The satisfaction levels of nurses receiving pressure injury training through the deep learning model and mobile application are higher than those using traditional training approaches.

H3: The deep learning model is more effective than conventional methods in the accurate detection and classification of pressure injuries.

METHODS

Study type: This research was structured as a randomized controlled experimental study aiming to develop a deep learning-based model for the identification and categorization of pressure injuries and to assess its impact on nurses' knowledge levels and training satisfaction.

Study group: The study included 80 nurses employed in the intensive care, internal medicine, and surgical units at Istanbul Beykent University Hospital between March and April 2022. The required sample size was determined through power analysis using G*Power 3.1, based on a prior similar study.[15] To achieve a 95% power with a 0.5 effect size and 5% error margin, a sample of 56 nurses (28 per group) was found to be adequate. Considering potential attrition, the sample was increased to 60 nurses, evenly distributed between experimental and control groups. Participants were selected using a simple randomization technique via the website http://stattrek.com/statistics/random-number-generator.aspx. The study purpose was explained to all participants, and informed consent was obtained from those who met the inclusion criteria: age above 18, employment in intensive care or clinical settings, and voluntary agreement to participate.

Outcome Measures: The data collection tools included the "Structured Nurse Introduction Form," the "Modified Pieper Pressure İnjury Knowledge Test," the "Braden Risk Assessment Scale," and the "Nursing Satisfaction Survey."

Structured Nurse Introduction Form: Designed based on literature, this form gathered demographic and professional background data of the nurses.

Modified Pieper Pressure Injury Knowledge Test**:** Originally developed by Pieper and Mott (1995) and later modified by Lawrence, this version was validated and adapted into Turkish by Gul et al. in by Gul et al. in 2017[16]. The 49-item scale includes three subdimensions: general knowledge (max 49 points), prevention knowledge (33 points), staging (9 points), and wound identification (7 points). Permission to use the modified version was obtained from Prof. Dr. Asiye Gül. Reliability analysis yielded Cronbach's alpha values of .838 for the experimental group and .812 for the control group.

Braden Risk Assessment Scale: Adapted for use in Turkey by Pınar and Oguz[17], this scale scores between 6 and 23. A score of ≤12 indicates high risk, 13–14 moderate risk, and 15–16 low risk.

Nursing Satisfaction Survey**:** Developed by the researchers in line with relevant literature, this 25-point Likert-type scale assessed nurses' satisfaction with the training. Reliability testing produced a Cronbach's alpha of .95.

Development of the Deep Learning Model: The proposed deep learning-based model, named BYT-CNN, was initially trained using 175 clinical images and demonstrated a classification accuracy of 97%. To improve performance, the training dataset was expanded to include 1,000 images (500 positive, 500 negative). The model pipeline included preprocessing (resizing to 224×224 pixels, normalization), data augmentation (rotation, zoom, flipping), and training with architectures such as ResNet, EfficientNet, VGG16, and a custom CNN built in TensorFlow.

The dataset was split 80/20 for training and validation. Adam optimizer, a 0.001 learning rate, batch size of 32, and 50 training epochs were used. The Categorical Crossentropy loss function was employed. Hyperparameters were tuned using grid search, and early stopping was implemented when validation loss plateaued for 10 epochs. Performance metrics included validation accuracy, loss, precision, recall, and F1-score. The best-performing model was integrated into a mobile app. The details of the developed model were published in an article.[18]

Pipeline Summary:

1. ***Image Capture:*** Photographs of pressure injuries or at-risk areas are taken via mobile devices.
2. ***Preprocessing:*** Images are resized, normalized, and augmented.
3. ***Prediction:*** The images are processed by trained CNN models for classification.
4. ***Output Generation:***
   Presence or absence of pressure injury
   If present, stage classification (per NPUAP guidelines)
   Prediction result sent to nurse's device within ~3 seconds
5. ***Care Recommendation:*** Nursing care suggestions are provided based on the stage via the mobile app.

This pipeline structured the training, validation, and clinical implementation processes, ensuring high applicability. The system enables classification based on the NPUAP Pressure Injury Staging System and delivers appropriate nursing care suggestions directly through the mobile app. Connectivity is established via Bluetooth or Wi-Fi, and results are communicated to the nurse's device within three seconds.

A real-world validation study was conducted, where the model was tested on new clinical images. Nurses uploaded wound images through the app, and the system's predictions were compared against clinical observations and Braden scores. Additionally, a team of expert nurses (≥5 years ICU experience) evaluated the results. Expert approval exceeded 90%, with risk assessment accuracy at 95% and stage classification accuracy at 86%, aligning with test-phase performance. Nurses reported high usability and utility of the system, with average assessment time being only 3 seconds.[18]

Procedures: Prior to data collection, the BYT-CNN model was developed. All nurses received a 4-hour standardized theoretical course on pressure injuries. One week later, participants were randomly assigned into control (traditional method) and experimental (deep learning model) groups. Pre-intervention assessments included the Structured Nurse Introduction Form and the Modified Pieper Pressure Injury Knowledge Test.

Control Group: Nurses used the Braden Scale to identify and classify pressure injuries. They received additional training using researcher-prepared written materials. Post-training, they completed a satisfaction survey and, one week later, a post-test. Following this, volunteer nurses from this group also tested the deep learning model.

Experimental Group: Nurses used the mobile app powered by the BYT-CNN model to detect and classify pressure injuries in clinical settings. The provided care recommendations based on detected stage. Post-intervention satisfaction surveys and knowledge post-tests were conducted one week later (Figure 1).

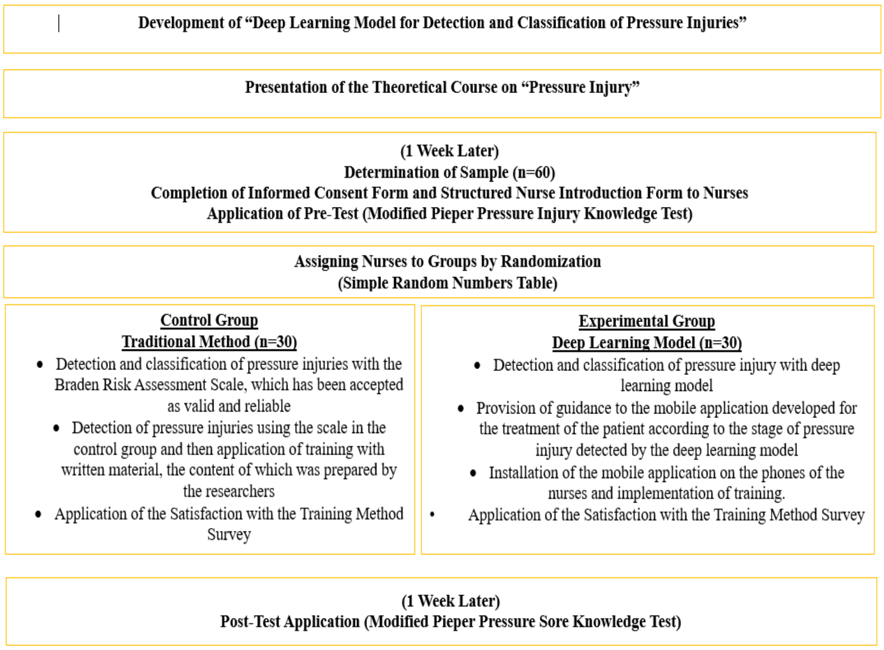

Figure 1: CONSORT Diagram

Statistical analysis: Data analysis was conducted using IBM Statistical Package for the Social Sciences (IBM SPSS Corp., Armonk, NY, USA) 25.0. Descriptive statistics included frequency, percentage, mean, and standard deviation. Chi-square and Fisher's exact tests were used for categorical variables, while independent and dependent t-tests were applied for continuous variables. Cronbach's alpha was calculated for scale reliability.

The study utilized deep learning approaches, particularly CNN-based models such as ResNet, VGG16, Inception, and EfficientNet. Traditional machine learning methods (e.g., SVM, k-NN) were considered suboptimal due to their limitations in visual pattern recognition. CNNs were selected for their ability to autonomously extract features from image data and make accurate multi-class predictions. The model was optimized for low-latency clinical applications, ensuring rapid real-time inference for nurses in high-paced environments.

Ethical considerations: Ethical approval was secured from the Istinye University Human Research Ethics Committee (Decision No: 2704, Date: 27.01.2021), and institutional permission was obtained from Beykent University Hospital (Document No: 14, Date: 08.02.2022). All participants gave informed consent. The study was registered as a clinical trial (ClinicalTrials.gov ID: NCT06641258). The interdisciplinary research team consisted of computer engineers, nursing faculty, and clinical practitioners. All code developed for the model is maintained in a private GitHub repository with version control. Due to data protection and patient confidentiality, this repository is accessible only within authorized environments.

RESULTS

The mean age of the nurses in the experimental group participating in the study was 25.67±7.270, and the control group was 25.10±3.478. 40% of the nurses in the experimental and control groups worked in surgical services. 33.3% of the nurses in the experimental group always encountered pressure injuries, and 33.3% of the nurses in the control group frequently encountered them. All of the nurses participating in the study stated that pressure injuries were the responsibility of the nurse (Table 1).

Table 1: Nurses Sociodemographic Characteristics (n=60)

Features		Experiment n	Experiment Mean±SD	Control n	Control Mean±SD
Age		30	25.67±7.270	30	25.10±3.478
		n	%	n	%
Gender	Male	0	0	0	0
	Woman	30	100	30	100
Hospital Unit Worked	Internal Units	7	23.3	11	36.7
	Surgical Sciences	12	40.0	11	36.7
	Intensive Care Unit	11	36.7	8	26.7
Pressure with injury encounter frequency	Always	9	30.0	10	33.3
	Often	10	33.3	8	26.7
	Sometimes	10	33.3	10	33.3
	None	1	3.3	2	6.7
Pressure injury Prevention And treatment of the nurse under the responsibility of being situation	Yes	30	100.0	30	100.0
	No	0	0	0	0

n: Number of participants, SD: Standard Deviation,

When the scores of the knowledge exam (pre-test) administered before the training were compared, the average score of the experimental group was 29.03±3.9 and the control group was 29.33±3.56. No statistically significant difference was found between the two groups, indicating that the groups were distributed homogeneously (P>.5) (Table 2).

When the nurses' post-training knowledge exam (post-test) scores were compared, the average score of the experimental group was determined as 39.36±1.88 and the control group as 33.30±1.68. The post-training knowledge level of the experimental group was found to be statistically significantly higher than the control group (P<.05) (Table 2).

Table 2: Nurses Modified Comparison of Pieper Pressure Injury Knowledge Test Mean Scores (n=60)

Modified Pieper Pressure Injury Knowledge Test		Experiment Mean±SD (Min-Max)	Control Mean±SD (Min-Max)	t	*P*
Pre -test	Total	29.03±3.95 (21-38)	29.33±3.56 (22-35)	-.795	.430 **
	Pressure wound prevention / risk	21.26±2.93 (16-27)	21.60±2.94 (16-27)	-.053	.958
	Staging	4.46±1.8 (1-8)	4.73±1.28 (2-7)	-2,040	.056
	Wound Describing	3.30±0.95 (2-5)	3.0±1.017 (1-5)	-.955	.344
Post-test	Total	39.36±1.88 (26-43)	33.30±1.68 (24-35)	-.796	.029*
	Pressure injury prevention/risk	19.63±1.47 (17-23)	17.36±1.99 (15-23)	-.313	.755
	Staging	10.86±0.73 (4-17)	7.63±1.24 (3-6)	-2,797	.007*
	Wound Identification	13.86±0.68 (3-15)	5.30±0.74 (2-6)	1,280	.006*

* Independent sample t-test ** One-Way ANOVA SD: Standard Deviation $P < .05$

When the satisfaction levels of the nurses participating in the study were examined, the mean score of the experimental group was determined as 24.60±0.96 and the control group as 20.93±0.63. The satisfaction level of the experimental group with the training was found to be statistically significantly higher than the control group (*P*<.05) (Table 3).

Table 3: Nurses From education Satisfaction Levels of Evaluation (n=60)

Feature	Experiment Mean±SD (Min-Max)	Control Mean±SD (Min-Max)	t	*P*
Nurses Satisfaction Level	24.6±0.96 (22-25)	20.9±0.63 (6-24)	.461	.040 **

* Independent sample t-test ** One-Way ANOVA SD: Standard Deviation *P* < .05

The control group determined the patients' risk levels as moderate with 13.83±4.67 using the Braden pressure injury risk assessment scale and that they were 50% successful in stage estimation (Table 4).

Table 4: Control Group Nurses' Braden Risk Assessment The scale Point Averages (n=30)

Feature	Experiment Mean±SD (Min-Max)	Control Mean±SD (Min-Max)
Braden Risk Assessment	0	13.83±4.67 (6-24)

It was determined that the experimental group was able to assess risk with 97% success and determine the wound stage with 89% prediction verification with the deep learning model (Figure 2). Although the overall accuracy rate of the deep learning model developed in the study is high, it has been observed that the accuracy rate falls below 75% in some individual images (Figure 2). This situation can generally be due to class imbalances in the data set, variability in image quality, or low visual discrimination of some stages (especially stage 1 and stage 2).

The precautions taken during the model development phase to prevent such low accuracy rates in real field applications are as follows:

a) Enrichment of the Data Set: It is planned to add more pressure injury images taken from different clinical conditions to the data set. Increasing the number of examples, especially for classes such as stage 1 and stage 2, will strengthen the class discrimination capacity of the model.

b) Improvement of Image Quality: During the data collection phase, the quality of the training data will be increased by filtering low-resolution, blurry or poorly lit images. In addition, techniques such as "noise reduction" will be used during data augmentation.

c) Advanced Augmentation Techniques: Advanced data augmentation methods such as Mixup and CutMix will be integrated to make the model more generalizable. In this way, the model's resilience to different variations will increase.

d) Use of Class Weighted Loss Function: By using a loss function that takes class weights into account in model training, learning of underrepresented classes will be encouraged. Thus, accuracy rates, especially in rare stages, can be increased.

e) Use of Ensemble Models: By applying ensemble methods that combine the outputs of different CNN architectures (e.g. ResNet, EfficientNet, VGG16), the prediction accuracy will be stabilized. This method helps compensate for individual model errors.

f) Model Update with Continuous Field Feedback: The model will be continuously updated with field feedback from nurses and new patient data during real use, so that the model continues to adapt to the field.

As a result, it is aimed to minimize low accuracy rates and to ensure that the model operates with high reliability and accuracy in the clinical field in line with these improvement strategies.

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Photo 10 = Estimated Stage = Stage 1, Accuracy Percentage = 71%
Photo 11 = Estimated Stage = Stage 3, Accuracy Percentage = 99%
Photo 12 = Estimated Stage = Stage 3, Accuracy Percentage = 99%
Photo 13 = Estimated Stage = 2nd Stage, Accuracy Percentage = 73%
Photo 14 = Estimated Stage = Stage 4, Accuracy Percentage = 99%
Photo 15 = Estimated Stage = Stage 1, Accuracy Percentage = 77%
Photo 16 = Estimated Stage = Stage 4, Accuracy Percentage = 77%
Photo 17 = Estimated Stage = Stage 4, Accuracy Percentage = 99%
Photo 18 = Estimated Stage = Stage 4, Accuracy Percentage = 86%
Photo 19 = Estimated Stage = Stage 4, Accuracy Percentage = 74%
Photo 1 = Estimated Stage = Stage 1, Accuracy Percentage = 99%
Photo 20 = Estimated Stage = Stage 4, Accuracy Percentage = 76%
Photo 21 = Estimated Stage = Stage 4, Accuracy Percentage = 99%
Photo 22 = Estimated Stage = Deep Tissue, Accuracy Percentage = 99%
Photo 23 = Estimated Stage = Deep Tissue, Accuracy Percentage = 99%
Photo 24 = Estimated Stage = Mucosa Membrane, Accuracy Percentage = 99%
Photo 25 = Estimated Stage = Mucosa Membrane, Accuracy Percentage = 99%
Photo 26 = Estimated Stage = Stage 1, Accuracy Percentage = 76%
Photo 27 = Estimated Stage = Unclassifiable, Accuracy Percentage = 99%
Photo 28 = Estimated Stage = Mucosa Membrane, Accuracy Percentage = 74%
Photo 29 = Estimated Stage = Dependent on Medical Device, Accuracy Percentage = 99%
Photo 2 = Estimated Stage = Stage 1, Accuracy Percentage = 74%
Photo 30 = Estimated Stage = Dependent on Medical Device, Accuracy Percentage = 94%
Photo 3 = Estimated Stage = Stage 1, Accuracy Percentage = 99%
Photo 4 = Estimated Stage = Stage 1, Accuracy Percentage = 97%
Photo 5 = Estimated Stage = Stage 2, Accuracy Percentage = 99%
Photo 6 = Estimated Stage = Stage 2, Accuracy Percentage = 99%
Photo 7 = Estimated Stage = Stage 2, Accuracy Percentage = 73%
Photo 8 = Estimated Stage = Stage 2, Accuracy Percentage = 98%
Photo 9 = Estimated Stage = Stage 3, Accuracy Percentage = 75%
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In [34]: result = printEvaluate(x_test, y_test, verbose = verbose)
2/2 [==============================] - 0s 68ms/step - loss: 0.2115 - accuracy: 0.8976
```

Figure 2: Experiment Group Nurses Deep Learning Model Risk Estimation with Levels (n=30)

DISCUSSION

Nurses are among the most important members of the healthcare team who care for patients for the longest period of time; they closely monitor care, especially in units such as intensive care and palliative care. Nursing care practices implemented for the prevention and treatment of pressure ulcers both promote healing and improve the quality of healthcare. Therefore, a thorough risk assessment is essential to prevent the development of pressure ulcers, which lead to morbidity and mortality. In cases where pressure ulcers cannot be prevented, it is crucial to properly identify and classify pressure ulcers and promptly provide appropriate nursing interventions to the patient.[4,9,25-28]

When the studies conducted in the literature for the prevention, detection, and treatment of pressure injuries are examined, it has been determined that innovative approaches such as artificial intelligence have been applied.[29-31] Based on this information, the results of our study support that the deep learning model, which is a sub-branch of artificial intelligence, plays an active role in the detection and classification of pressure injuries.

The mean age of the nurses in the experimental group participating in the study was 25.67±7.270, and the control group was 25.10±3.478. 40% of the nurses in the experimental and control groups worked in surgical wards, 33.3% of the nurses in the experimental group always encountered pressure injuries, 33.3% of the nurses in the control group frequently encountered them, and all of the nurses participating in the study stated that pressure injuries were the responsibility of the nurse (Table 1). The sociodemographic characteristics of the nurses participating in the study are similar to the studies conducted.[29-31]

When the scores of the knowledge exam (pre-test) administered before the training were compared, the average score of the experimental group was determined as 29.03±3.9 and the control group as 29.33±3.56. No statistically significant difference was found between the two groups, indicating that the groups were distributed homogeneously (P>.05) (Table 2). When the scores of the knowledge exam (post-test) of the nurses were compared after the training, the average score of the experimental group was determined as 39.36±1.88 and the control group as 33.30 ± 1.68. The knowledge level of the experimental group after the training was found to be statistically significantly higher than the control group (P<.05) (Table 2). Studies report that deep learning and mobile applications have an improving effect on the detection, classification, care, and treatment of pressure injuries and support the results of our study.[14,18,31] Seo et al.[30] stated that they could minimize the inconsistencies in nurses' assessments of pressure injury stages classification with the deep learning model they developed. Jiang et al.[31] stated in their systematic review that machine learning, which forms the basis of artificial intelligence, was effective in detecting pressure injuries in studies conducted with machine learning. Shepherd et al.[32] stated that the detection, staging, and treatment of pressure injuries would be more effective using information technologies. Garcia-Zapirain et al.[33] developed a mobile application for the non-contact assessment of pressure injuries and found that this application allows staging of injuries, obtaining relevant information for diagnosis, and monitoring the development of injuries. The findings obtained from the literature support the findings of the study. According to these results, Hypothesis 1 was confirmed.

When the satisfaction levels of the nurses participating in the study were examined, the mean score of the experimental group was determined as 24.60±0.96 and the control group as 20.93±0.63. The satisfaction level of the experimental group with the training was found to be statistically significantly higher than the control group (P<.05) (Table 3). Studies have reported that the satisfaction level of the training given with the deep learning model and mobile application is higher than the traditional method and supports the results of our study.[33,34,35] Jayakumar et al.[36] stated that the satisfaction level of the artificial intelligence-supported decision-making model training they developed was superior to the traditional method. The findings obtained from the literature support the findings of the study. According to these results, Hypothesis 2 was confirmed.

The control group determined the patients' risk levels as moderate with 13.83±4.67 with the Braden pressure injury risk assessment scale and were 50% successful in stage estimation (Table 4). It was found that the experimental group could assess risk with 97% success with the deep learning model and determine the wound stage with 89% prediction verification. Studies report that the deep learning model is more successful than the traditional method in the detection and classification of pressure injuries and support the results of our study.[1,29,36,37,38] Wu et al.[39] developed an easy and programming-free artificial intelligence modeling tool capable of professional assessment for the detection of pressure injuries and independently performed by nurses, and stated that the model achieved an accuracy of 89% in the preliminary evaluation. Alderden et al.[40] stated that traditional risk assessment tools such as the Braden Scale may generally fail to capture factors specific to intensive care units, which may limit the prediction accuracy. In this context, they revealed that machine learning can be effective, especially in intensive care units. Anderson et al.[41] determined that they better identified the risk of pressure injuries with machine learning. Song et al.[42] used more than one machine learning model for the artificial intelligence model they developed for the detection of pressure injuries. The random forest model showed the best performance and found that it achieved 92% and 94% accuracy in the prediction of pressure injuries in two test sets, respectively. Pei et al.[37] stated that artificial intelligence models showed an extraordinary performance (95%) in predicting pressure injuries in their meta-analysis study examining machine learning-based prediction models for pressure injuries. Liu et al.[38] stated that the classification of pressure injuries with the deep learning model was successful and that it was an important tool for inexperienced nurses. The findings obtained from the literature support the findings of the study. According to these results, Hypothesis 3 was confirmed.

Study Limitations and Strengths: Randomly assigning patients to groups, having a control group, implementing nursing interventions in line with the literature, having a suitable environment that prevents nurses from being influenced by each other during the application, and allocating time for nurses to implement different applications after the study is completed.

The lack of hands-on practice prior to implementation may have negatively influenced nurses' confidence and performance.

CONCLUSION

Pressure injuries are clinical indicators that affect both patient outcomes and healthcare costs. Effective prevention involves risk assessment, skin care, nutrition, repositioning, mobilization, and education. These efforts require a multidisciplinary team, with nurses playing a central role.

This study demonstrated that the deep learning–based BYT-CNN model was more effective than conventional methods in improving nurses' knowledge, increasing satisfaction with training, and enhancing the accuracy of pressure injury detection and staging. Integrating artificial intelligence into nursing care can reduce diagnostic variability, improve patient safety, and support evidence-based practice.

As healthcare technology evolves, it is crucial for nurses and other health professionals to embrace innovation and incorporate AI-supported tools into clinical routines. Doing so not only increases the quality of care but also elevates the visibility and impact of the nursing profession. Future studies may explore broader applications of AI in other areas of nursing care and assess long-term clinical outcomes.

Ethics Committee Approval: Ethics committee approval was received for this study from the ethics committee of İstinye University Human Research Ethics Committee (Date: 27.01.2021, Number: 2704).

Informed Consent: The study purpose was explained to all participants, and informed consent was obtained from those who met the inclusion criteria: age above 18, employment in intensive care or clinical settings, and voluntary agreement to participate.

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Author Contributions: Concept – HK, AY, MD; Design – HK, AY, MD; Data Collection – HK, AY, MD; Data Analysis – AY, UK, RÇ; Data Interpretation – AY, UK, RÇ; Writing the article – HK, MD; Critical revision for important intellectual content – HK, AY, MD; Final approval – HK, AY, MD, UK, RÇ

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