Journal of Infrastructure, Policy and Development 2024, 8(8), 2687
https://doi.org/10.24294/jipd.v8i8.2687

Article

Loss of consciousness detection model for smart triage

Reem Alharthi[1,2,*], Mohammed Qadrouh[3], Wadee Alhalabi[1]

[1] Computer Science Department, King AbdulAziz University, Jeddah 21589, Saudi Arabia
[2] Applied College, University of Hafr Albatin, Hafr Albatin 39524, Saudi Arabia
[3] Ministry of Health, Makkah 11176, Saudi Arabia
*** Corresponding author:** Reem Alharthi, rmalharthi@uhb.edu.sa

CITATION

Alharthi R, Qadrouh M, Alhalabi W. (2024). Loss of consciousness detection model for smart triage. Journal of Infrastructure, Policy and Development. 8(8): 2687. https://doi.org/10.24294/jipd.v8i8.2687

ARTICLE INFO

Received: 25 August 2023
Accepted: 26 April 2024
Available online: 14 August 2024

Abstract: Falling is one of the most critical outcomes of loss of consciousness during triage in emergency department (ED). It is an important sign requires an immediate medical intervention. This paper presents a computer vision-based fall detection model in ED. In this study, we hypothesis that the proposed vision-based triage fall detection model provides accuracy equal to traditional triage system (TTS) conducted by the nursing team. Thus, to build the proposed model, we use MoveNet, a pose estimation model that can identify joints related to falls, consisting of 17 key points. To test the hypothesis, we conducted two experiments: In the deep learning (DL) model we used the complete feature consisting of 17 keypoints which was passed to the triage fall detection model and was built using Artificial Neural Network (ANN). In the second model we use dimensionality reduction Feature-Reduction for Fall model (FRF), Random Forest (RF) feature selection analysis to filter the key points triage fall classifier. We tested the performance of the two models using a dataset consisting of many images for real-world scenarios classified into two classes: Fall and Not fall. We split the dataset into 80% for training and 20% for validation. The models in these experiments were trained to obtain the results and compare them with the reference model. To test the effectiveness of the model, a *t*-test was performed to evaluate the null hypothesis for both experiments. The results show FRF outperforms DL model, and FRF has same accuracy of TTS.

Keywords: emergency; fall; involuntary falls; deep learning; machine learning (ML); pose estimation; random forest (RF); smart emergency department; syncope; triage

1. Introduction

Emergency departments (EDs) provide primary treatment for various patients suffering from a wide range of diseases and injuries, which vary in severity and risk. With an increasing number of admitted patients, EDs have become overcrowded, operating beyond their capacity, leading to a deterioration in the quality of care, extended waiting periods, delayed diagnosis and treatment, deterioration of some patient conditions, increased costs, and patient dissatisfaction (Gebrael et al., 2023). The growing number of patients affects triage, forcing patients with varying conditions to wait for hours, potentially leading to a loss of consciousness (Fekonja et al., 2023). Loss of consciousness is a common and serious indicator that requires high-priority triage (Queirós et al., 2021; Zaboli et al., 2022). When a patient loses consciousness, he or she becomes unbalanced, which result in falls. There is a strong relationship between loss of consciousness and falls (Aamir, 2024).

The World Health Organization (WHO) (2021) classifies falls as the second most common cause of death. Fall cases are serious problems, any delay in treatment negatively impacts patient health and safety (Hussain et al., 2019; Thakur and Han, 2021). The role of triage is to make accurate and quick decisions. With the influx of patients, it becomes challenging to promptly address cases of falls. Normally triage is performed with a primary reliance on human judgment. There is an essential medical need for triage improvement (Wretborn et al., 2023; Zachariasse et al., 2019).

Many solutions were proposed, one solution is to use AI techniques. Many medical studies have suggested the use of digital triage systems and their enhancement through the application of artificial intelligence techniques (Defilippo et al., 2023; Joseph et al., 2023; Kim et al., 2018; Queirós et al., 2021; Zaboli et al., 2022). Nevertheless, the use of Machine Learning (ML) and Deep Learning (DL) is expected to gradually spread in healthcare to include all medical specialties (Aamir, 2024; American College of Surgeons, 2019). It is possible to apply DL techniques to the visible symptoms of patients to support making decisions in triage.

ML techniques offer valuable solutions for dealing with patient triage in emergencies. This means that they can achieve an imposed leap in the quality of services provided to patients and directly improve the experiences in triage (Chen et al., 2023; Elhaj et al., 2023). Many medical studies have proposed the urgent need to address and improve triage, especially through the use of ML and DL (Fekonja et al., 2023; Gebrael et al., 2023; Thakur and Han, 2021; Zachariasse et al., 2019). The accuracy and effectiveness of triage can be increased by developing ML and DL models, thereby improving patient outcomes (Aamir et al., 2023; Chen et al., 2023; Elhaj et al., 2023). ML can also be applied to historical patient records to provide highly accurate and immediate assistance in decision-making for emergency doctors (American College of Surgeons, 2019; Ghosh et al., 2018; Mueller et al., 2022; Thakur and Han, 2021; Weng et al., 2017).

In this context, this paper proposes a framework for vision-based DL that classifies the patient's condition into two classes, fall and no fall, using pose estimation techniques. We investigate the effectiveness of ML models and DL to enhance and improve the triage process for fall cases. The aim of this work is to leverage the capabilities of DL to train a model that detects patient falls, calling for an immediate response based on the suggestion provided by the model. We hypothesis that DL model has the ability to detect fall cases as emergency staff. This could help in providing timely medical intervention. Therefore, this study proposes an intelligent vision-based triage system to detect the patient's fall state using DL models.

2. Literature review

Several recent studies have been conducted on various systems for fall detection, relying on wearable sensors, vision-based, DL algorithms, and ML techniques (Amsaprabhaa, 2023; Li et al., 2023; Wang et al., 2023; Wu et al., 2023; Zhang et al., 2023).

Leone et al. (2023) developed an automatic system based on a three-axis accelerometer was developed to recognize the four analyzed postures (standing, sitting, bending, and lying down), which is useful in detecting potentially inappropriate behavioral habits in the elderly. The system used ML algorithms to recognize postures in real-time and has been optimized to perform highly on low-computational power and energy-consuming platforms. The program was integrated and tested on two low-cost embedded systems (Raspberry Pi 4 and Odroid N2+). The testing phase involved several ML classifiers pre-trained using data from seven elderly users. The initial results showed an activity classification accuracy of around 98% for the four analyzed postures.

In the study of Vallabh et al. (2016), various classification methods were implemented for detecting falls and were able to differentiate between Activities of Daily Living (ADL) and falling activities using the "MobiFall" dataset. The data was pre-processed using medium and low pass filters. A filter rank-based system was applied to extract the first five features to optimize algorithmic dimensions. The five classification methods implemented were: Navie Bayes, k-NN, ANN (Artificial Neural Network), SVM (Support Vector Machine), and LSM. The k-NN method, with k equal to 5, achieved the highest accuracy of 87.5% compared to other classification methods.

Waheed et al. (2021) proposed a Fall Detection System (FDS) using DL, which collects information from wearable sensors to distinguish falls from routine activities to provide immediate medical assistance. The proposed system uses recurrent neural networks (RNNs) with Bidirectional Long Short-Term Memory (BiLSTM), to implement FDS on wearable sensors. Data was collected from both multi-media and single-media sources to simulate real-life activities.

In the research of Thakur and Han (2021) the authors proposed a fall detection system for the elderly based on Internet of Things (IoT). The study was conducted on two different datasets, and the results showed that among all ML methods, the K-NN is the most suitable for developing fall detection systems in terms of performance accuracy. The study also showed that the use of k-folds cross-validation and the AdaBoost algorithm improved the accuracy performance of the fall detection system based on the k-NN classifier, providing superior accuracy results compared to previous studies.

Kulurkar et al. (2023) proposed a novel system based on the IoT that utilizes low-power wireless sensors for networks and big data, cloud computing, and smart devices to detect fall incidents among the elderly in real-time. A three-axis accelerometer embedded in a wearable device is employed for this purpose, tasked with collecting data from seniors' movements in real-time. The sensor signals are processed and analyzed using a ML model on an advanced IoT gateway to achieve high efficiency in fall detection. The model was built and trained using the "MobiAct" published dataset, boasting an impressive accuracy rate of 95.87%.

Inturi et al. (2023) presented a solution for fall detection using vision-based methods. In this approach, they analyzed the human joint points, which are considered the main indicators of movement. A set of key points for the subject is obtained by applying a pre-trained AlphaPose network. These key points are inferred to be the common points of the subject. The acquired key points are processed through a framework of convolutional neural networks (CNN) layers with the assistance of LSTM architecture. The proposed solution detects five types of falls and six types of daily life activities. The study used the UP-FALL fall detection dataset to validate the fall detection system.

Chen et al. (2020) proposes a vision-based approach for fall detection by extracting human skeletal information using OpenPose. Three significant indicators can be identified: the falling speed at the center of the hip joint, the angle of the human body's central line with the ground, and the width-to-height ratio of the human body's external rectangle. The study utilized non-publicly available dataset.

Additionally, other studies of both approaches sensor and vision-based indicated that using RF helps to enhance the results (Hassan et al., 2023; Rezaei et al., 2023; Shilaskar et al., 2023).

3. Methodology

In this study, we propose a DL model that detects patient's fall in the ED. Our model is based mainly on dimensionality reduction. Our hypothesis indicates that the fall data has too many low information features. The removal of such features will have a dramatic impact on the final result of the model. Feature Reduction for Fall model (FRF) is a DL model with dimensionality reduction. The model is shown in **Figure 1**. For this reason, H_0: $\mu_1 = \mu_2$.

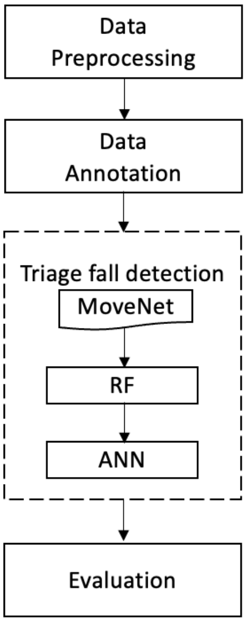

Figure 1. The proposed FRF model.

(a) **(b)**

Figure 2. Dataset example of cases with and without falling. **(a)** Not fall case; **(b)** fall case.

Data preprocessing and annotation:

We collected 536 images as a dataset for the detection of patients' falls in triage. We intentionally collected balanced data from diverse online sources. This new dataset we call VisFall23. VisFall23 has images address two categories "Fall" and "Not Fall". The first category comprises images illustrating individuals engaged in various physical activities such as walking, bending, and sitting. The second category has a variety of positions associated with falling to the ground. **Figure 2** shows samples of each of the two categories.

The dataset was split and annotated into two categories by the nursing team. The first category "Fall", consists of 268 images of people in falling situations.

The second category "Not fall", consists of 268 images of people in a not fallen situation.

Triage Fall Detection:

Since the study aims to detect patient falls, the methodology was designed to rely on human pose estimation, which is based on computer vision techniques. This is typically achieved by tracking 17 keypoints on the human body. These key points represent joints such as the wrists, knees, etc., as illustrated in **Figure 3**.

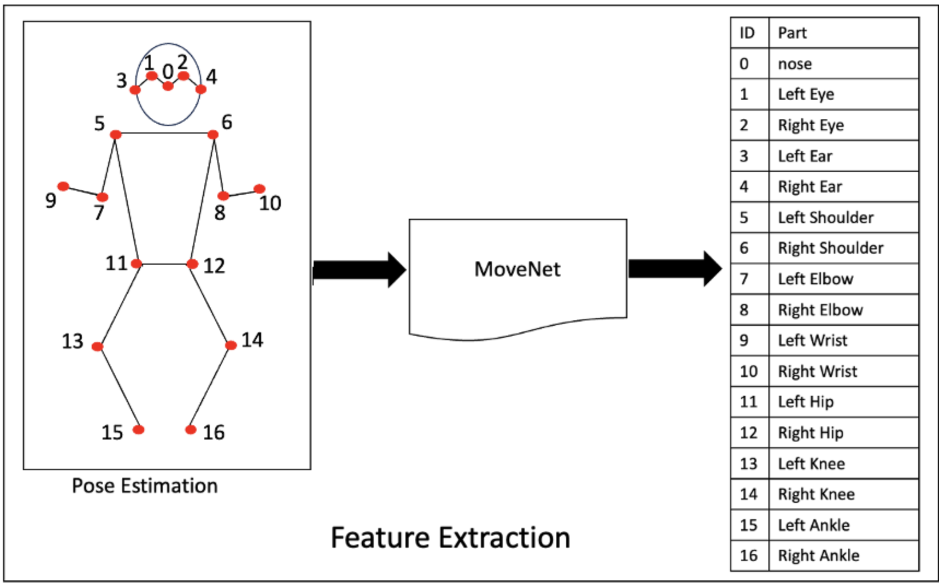

Figure 3. Pose estimation for human body with 17 keypoints used in triage fall detection.

MoveNet:

The methodology uses a vision-based approach, where a DL model is trained using CNN to classify the state of emergency patients who lose control of their bodies and fall. The DL process for pose estimation uses on CNN algorithms. CNNs are used for image recognition and feature detection, allowing them to extract the features that determine the patient's fall state. This enables the detection of patient fall case by analyzing the movement of the 17 keypoints illustrated in **Figure 3**.

Pose estimation models take processed camera images as inputs and output information about key points. The detected keypoints are indexed using fragment ID, with a confidence score ranging from 0.0 to 1.0. The confidence score indicates the likelihood of a keypoint being present at that position.

During feature extraction, all candidate keypoints are generated for the classification of the patient's fall state. The movement of the relevant key points on the patient can be tracked by observing changes in their positions in each frame of the video, reflecting the patient's body movement. Through MoveNet, the aforementioned keypoints are extracted as shown in **Figure 3**. MoveNet exports the processed key points in a digital value format for each joint, typically in a comma-separated value (CSV) file.

Figure 4 shows the DL model workflow which consists of the CNN and ANN algorithms, whereas our other model **Figure 1** has the (RF) as an extra phase to do the dimensionality reduction.

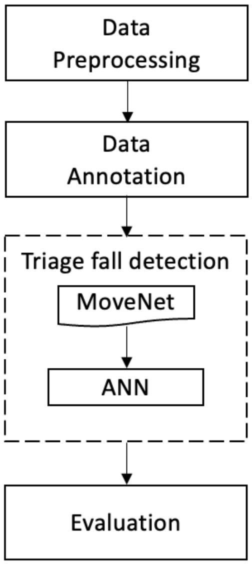

Figure 4. DL model workflow.

Since our model is a binary classification model for the triage fall detection, the falling class was assigned a value of 0 and labelled "Fall," while the not-falling class was assigned a value of 1 and labelled "Not fall."

The model was trained with labelled data for the two models. **Figure 5** shows the results of pose estimation phase. The DL model deals with all the data exported from MoveNet, with 51 features for each image.

(a) **(b)**

Figure 5. Samples of dataset. **(a)** Example of a "Not Fall" class with keypoints illustrated; **(b)** example of a "Fall" class with keypoints illustrated.

RF for feature reduction:

Feature reduction process was conducted on the RFR model where we use RF to analyzes the features through feature selection and select the most impactful features in determining the patient's position. Feature selection phase has selected 15 features. **Figure 6** illustrates the feature in descending order to determine the patient's position.

According to many studies that suggest using RF feature selection yields to improve performance metrics (Nguyen et al., 2013; Zhao et al., 2022).

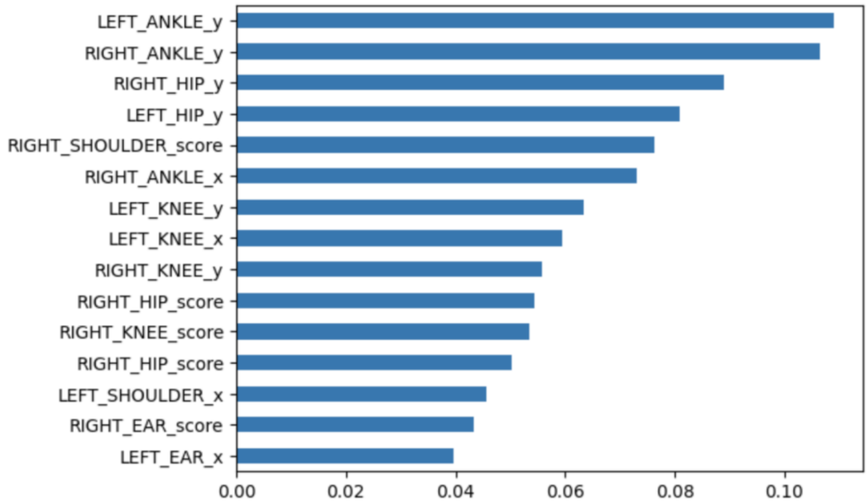

Figure 6. The top 15 features selected by feature importance phase.

ANN:

The experiment was conducted using TensorFlow Lite and Keras (Machine and Data, 2021). The data was split into two sets, with 80% assigned for training and 20% for validation. Both models use the following layers:

1) The input layer with Tanh activation function,
2) Hidden layers embedded with the Tanh activation function, and
3) The output layer with SoftMax activation function.

4. Result and discussion

To run the two models and see the results, various tools and techniques were used as shown in **Table 1**.

Table 1. Tools and techniques used in the triage fall detection model.

Tool/Technique	Description
Pose estimation	Human pose estimation to track and detect human movements.
TensorFlow	Framework supports ML models used for building AI and solving problems like detecting human poses.
Key points	Human joints (a.k.a landmarks) like wrists, knees, and shoulders.
Keras	A high-level API build on the Python neural network library that offers a user-friendly and modular approach to building deep learning models
MoveNet	An ultra-fast model that is able to accurately detect the 17 key points of a body.
Feature Importance	ML technique used to evaluate the significance and impact of various features in predicting the target variable (Nguyen et al., 2013; Zhao et al., 2022).

The images were imported into MoveNet for the extraction of 17 keypoints. MoveNet generates features related to the 17 keypoints, totaling 51 features.

For both models, we did comparative analysis to evaluate the performance. The confusion matrix was used to measure the performance of DL model against FRF model based on accuracy, specificity, and sensitivity. **Figure 7** shows the confusion matric classification measure representation.

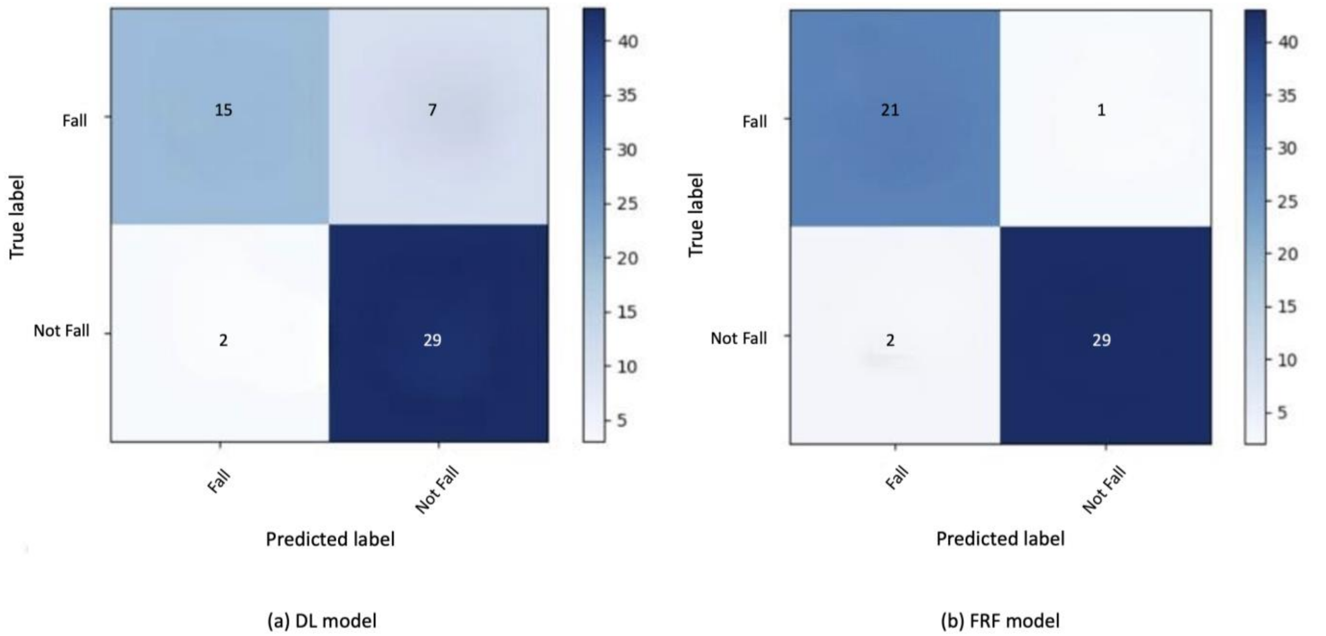

Figure 7. Confusion matrix of triage fall detection.

The DL model achieved 82% accuracy, **Figure 8** shows a visual representation of the training and validation sets.

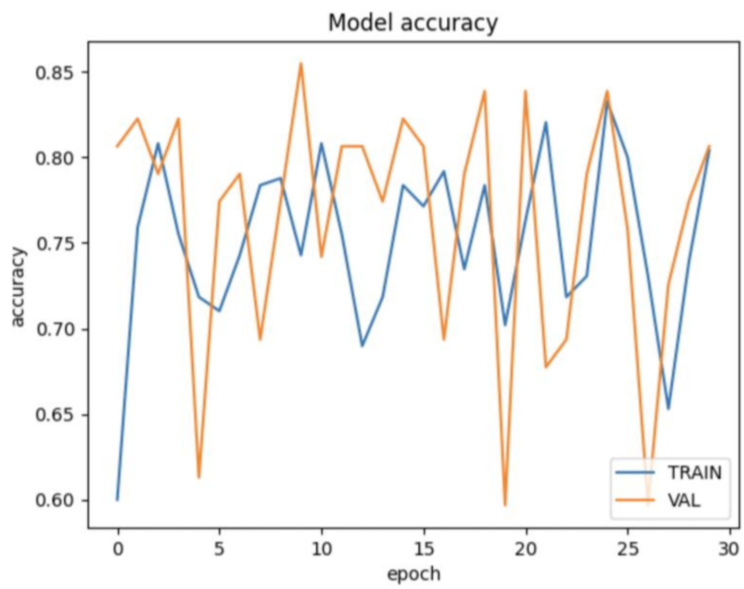

Figure 8. Plot of accuracy for train and validate sets for DL model.

The second model FRF shows an accuracy of 94%. **Figure 9** presents the visual representation of the training and validation sets.

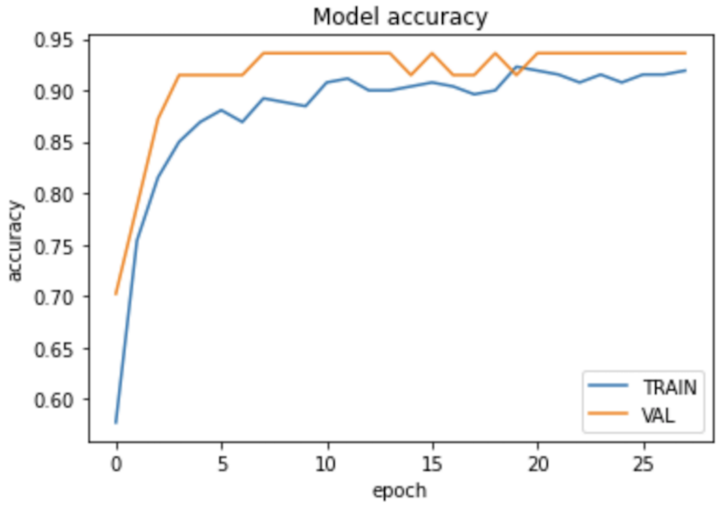

Figure 9. Plot of accuracy for train and validate set for FRF model.

Table 2 shows the performance result for a) DL model, b) FRF model. As seen in **Figure 10** the results show the superiority of the FRF model and its ability to generalize better. **Figure 10** shows the accuracy of both models. We can conclude that the result is due to the use of feature importance RF. The use of the RF layer enhanced fall detection decision-making, which support our claim that in hypotheses.

Table 2. The performance metrics for the two experiments DL model and FRF.

Classification model	Accuracy	Specificity	Sensitivity	F1 score
a) DL model	82	65	82	72
b) FRF model	94	91	94	92

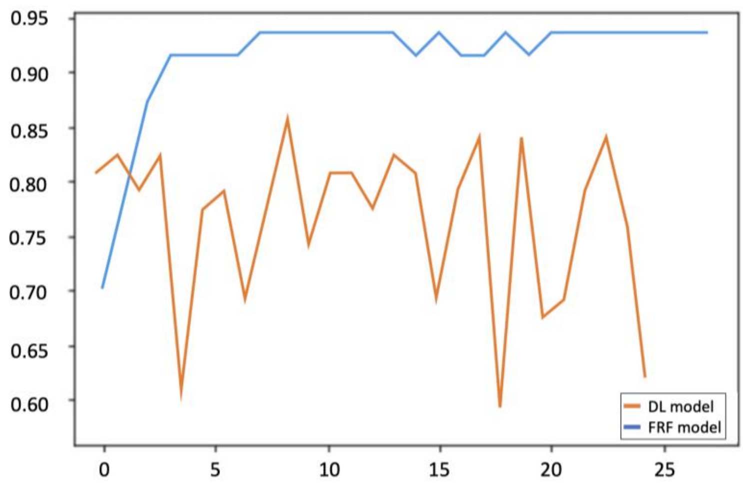

Figure 10. Accuracy plot for DL model and FRF model.

Statistical Analysis:

In order to conduct the *T*-test, we collected more 40 new samples that represent scenarios in which there were "falls" and "not falls". $N = 40$ images in each group splitting them into two group. The sample was intended to perform a comparative analysis between two distinct groups: control group and test group.

a. DL model:

Control group (nursing evaluation), and test group (DL model). The result of *T*-test shows that *p*-value = 0.0089 which is <0.05, confidential interval reaches 95% from the range 0.08 to 0.51, which indicates there is statistical difference between the assessing of nursing team (control group) and FFM assessing (test group).

Confidence interval does not include zero value in the range of 0.08 to 0.15, which indicates there is a very effect on data. t value = 2.7320 and degree of freedom (df) = 46 and standards error of difference =0.107.

As shown in **Table 3** the mean in control group higher than the mean in test group. Furthermore, the standard deviation (SD) is smaller in the control group which indicates less variability and higher precision in the mean. the standard error of the mean (SEM) in control group is smaller than SEM in test group. All this observation led to reject the null hypothesis for FFM.

b. RFR model:

In addition, to what we showed in experiment #1 that FRF model Control group (nursing evaluation), and test group (FRF). The *p*-value = 0.3110 which is >0.05, confidential interval reaches 95% from the range −0.05 to 0.15, which indicates there is no statistical difference between the assessing of nursing team (control group) and FRM assessing (Test group)

Confidence interval includes zero value in the range of 0.05 to −0.15, which shows there is no static and important effect on data.

After analyzing the means, SD, and SEM on control and test groups results as shown in **Table 3**, we notice the following:

Mean for control group is 0.98 while mean for test group is 0.93. This shows that control group, achieved higher results compared to test group in mean.

RFR outperform the DL model, DL model.

SD for control group (0.16) is less than the SD for test group (0.27). This shows that results in control group are more concentrated around the mean, while the results in the test group are more distributed.

SEM for control group (0.02) is less than SEM result for test group (0.04), which shows that the mean of control group could be more accurate.

Based on the above, it’s clear that FRF doesn’t vary a lot from the nursing team. Thus, null hypothesis cannot be rejected for FRF.

Table 3. *T*-test for the two groups for both models.

Model		Control group	Test group	*p*-value
DL model	Mean	0.98	0.67	0.0089
	SD	0.20	0.48	
	SEM	0.04	0.10	
FRF model	Mean	0.98	0.93	0.3110
	SD	0.16	0.27	
	SEM	0.02	0.04	

To evaluate the performance of our algorithm FRF, we compare it with the existing method currently used in emergency department in hospital and carried out by human triage system and other systems mentioned (Leone et al., 2023; Rezaei et al., 2023; Zhang et al., 2023). **Table 4** shows the comparison of our suggested models with other approaches in literature.

Table 4. Comparison of our proposed models with existing approaches in the literature.

Method	Accuracy
Based on human detection (Zhang et al., 2023)	77
Based on human keypoints (Zhang et al., 2023)	83
Image-based fall detection (Zhang et al., 2023)	90
RF (Leone et al., 2023)	98
RF (Rezaei et al., 2023)	92
DL model	82
FRF model	94

In Leone et al., 2023 and (Rezaei et al., 2023) the accuracy values for sensor-based methods while (Zhang et al., 2023) is vision-based method. We present our models to triage in ED the other study applied for different field. Moreover, FRF model achieved higher result in accuracy than method in (Zhang et al., 2023).

As shown in **Table 2**, using dimensionality reduction in FRF was important to refine the triage fall detection accuracy and improve its computational efficiency with an overall accuracy of 94%, which is 12% higher than the DL model. We also used a balanced data for both classes. Hence, the FRF proves it can be as good as human classification and the result of the statistical analysis shows in **Table 3**.

5. Conclusion

DL has the abilities to improve prioritize patient upon their condition in emergency department. We introduced a vision-based triage fall detection model that detects emergency departments patient's falls. RF in conjunction with DL algorithms enhanced the accuracy of triage fall detection. The dataset consisted of 536 images of different body poses including falling. The images were divided into two groups: 80% for training and 20% for validation. The statistical analysis achieved an accuracy of 94%, a specificity of 91%, and a sensitivity of 94%. Despite a small data volume, this level of accuracy was never reached using the CNN with the fully feature of 17 key points. The results of an RF on feature selection show the value of DL methods in CNN feature selection over fully features. We used the dimensionality reduction for keypoints analysis with triage staff as a means of comparison. The findings suggest that feature dimensionality reduction has the same level of accuracy in fall detection as TTS. The model could be improved in the future to assess the impact of the patient's fall and the severity of their loss of consciousness.

Author contributions: Conceptualization, RA and MQ; methodology, RA; software, RA; validation, WA, MQ and RA; formal analysis, RA; investigation, RA; resources, WA; data curation, MQ; writing—original draft preparation, RA; writing—review and editing, WA; visualization, WA; supervision, WA; project administration, RA;

funding acquisition, WA. All authors have read and agreed to the published version of the manuscript.

Funding: This project was funded by Deanship of Scientific Research (DSR) at King Abdulaziz University, Jeddah under grant No. (IFPIP-1110-611-1443), the authors, therefore, acknowledge with thanks DSR technical and financial support.

Data availability: The data that support the findings of this study are available on request from the corresponding author, Alharthi.

Conflict of interest: The authors declare no conflict of interest.

References

Aamir, A., Jamil, Y., Bilal, M., et al. (2024). Artificial Intelligence in Enhancing Syncope Management—An Update. Current Problems in Cardiology, 49(1), 102079. https://doi.org/10.1016/j.cpcardiol.2023.102079

American College of Surgeons. (2019). AI outperforms clinicians' judgment in triaging postoperative patients for intensive care. ScienceDaily. Available online: www.sciencedaily.com/releases/2019/10/191029182456.htm (accessed on 21 March 2023).

Chen, W., Jiang, Z., Guo, H., et al. (2020). Fall Detection Based on Key Points of Human-Skeleton Using OpenPose. Symmetry, 12(5), 744. https://doi.org/10.3390/sym12050744

Chen, Y., Chen, H., Sun, Q., et al. (2023). Performance of machine learning models in identifying and predicting patients' need for intensive care in emergency department triage: A systematic review. The American Journal of Emergency Medicine, 73, 166–170.

Defilippo, A., Bertucci, G., Zurzolo, C., et al. (2023). On the computational approaches for supporting triage systems. Interdisciplinary Medicine, 1(3). https://doi.org/10.1002/inmd.20230015

Elhaj, H., Achour, N., Tania, M. H., et al. (2023). A comparative study of supervised machine learning approaches to predict patient triage outcomes in hospital emergency departments. Array, 17, 100281. https://doi.org/10.1016/j.array.2023.100281

Fekonja, Z., Kmetec, S., Fekonja, U., et al. (2023). Factors contributing to patient safety during triage process in the emergency department: A systematic review. Journal of Clinical Nursing, 32(17–18), 5461–5477. https://doi.org/10.1111/jocn.16622

Gebrael, G., Sahu, K. K., Chigarira, B., et al. (2023). Enhancing Triage Efficiency and Accuracy in Emergency Rooms for Patients with Metastatic Prostate Cancer: A Retrospective Analysis of Artificial Intelligence-Assisted Triage Using ChatGPT 4.0. Cancers, 15(14), 3717. https://doi.org/10.3390/cancers15143717

Ghosh, E., Eshelman, L., Yang, L., et al. (2018). Early Deterioration Indicator: Data-driven approach to detecting deterioration in general ward. Resuscitation, 122, 99–105. https://doi.org/10.1016/j.resuscitation.2017.10.026

Hassan, C. A. U., Karim, F. K., Abbas, A., et al. (2023). A Cost-Effective Fall-Detection Framework for the Elderly Using Sensor-Based Technologies. Sustainability, 15(5), 3982. https://doi.org/10.3390/su15053982

Hussain, F., Umair, M. B., Ehatisham-ul-Haq, M., et al. (2020). An Efficient Machine Learning-based Elderly Fall Detection Algorithm. arXiv. https://doi.org/10.21203/rs.3.rs-39065/v1

Inturi, A. R., Manikandan, V. M., & Garrapally, V. (2022). A Novel Vision-Based Fall Detection Scheme Using Keypoints of Human Skeleton with Long Short-Term Memory Network. Arabian Journal for Science and Engineering, 48(2), 1143–1155. https://doi.org/10.1007/s13369-022-06684-x

Joseph, J. W., Leventhal, E. L., Grossestreuer, A. V., et al. (2023). Machine Learning Methods for Predicting Patient-Level Emergency Department Workload. The Journal of Emergency Medicine, 64(1), 83–92. https://doi.org/10.1016/j.jemermed.2022.10.002

Kim, D., You, S., So, S., et al. (2018). A data-driven artificial intelligence model for remote triage in the prehospital environment. PLOS ONE, 13(10), e0206006. https://doi.org/10.1371/journal.pone.0206006

Kulurkar, P., Dixit, C. kumar, Bharathi, V. C., Monikavishnuvarthini, A., et al. (2023). AI based elderly fall prediction system using wearable sensors: A smart home-care technology with IOT. Measurement: Sensors, 25, 100614. https://doi.org/10.1016/j.measen.2022.100614

Leone, A., Rescio, G., Caroppo, A., et al. (2023). Human Postures Recognition by Accelerometer Sensor and ML Architecture Integrated in Embedded Platforms: Benchmarking and Performance Evaluation. Sensors, 23(2), 1039.

https://doi.org/10.3390/s23021039

Li, Y., Zuo, Z., & Pan, J. (2023). Sensor-based fall detection using a combination model of a temporal convolutional network and a gated recurrent unit. Future Generation Computer Systems, 139, 53–63. https://doi.org/10.1016/j.future.2022.09.011

M, A., Y, N. J., & H, K. N. (2023). Multimodal spatiotemporal skeletal kinematic gait feature fusion for vision-based fall detection. Expert Systems with Applications, 212, 118681. https://doi.org/10.1016/j.eswa.2022.118681

Machine, D., & Data, L. M. U. H. (2021). AI for Healthcare with Keras and Tensorflow 2.0, 1st ed. Apress.

Mueller, B., Kinoshita, T., Peebles, A., et al. (2022). Artificial intelligence and machine learning in emergency medicine: a narrative review. Acute Medicine & Surgery, 9(1). https://doi.org/10.1002/ams2.740

Nguyen, C., Wang, Y., & Nguyen, H. N. (2013). Random forest classifier combined with feature selection for breast cancer diagnosis and prognostic. Journal of Biomedical Science and Engineering, 06(05), 551–560. https://doi.org/10.4236/jbise.2013.65070

Queirós Pokee, D., Barbosa Pereira, C., Mösch, L., et al. (2021). Consciousness Detection on Injured Simulated Patients Using Manual and Automatic Classification via Visible and Infrared Imaging. Sensors, 21(24), 8455. https://doi.org/10.3390/s21248455

Rezaei, A., Mascheroni, A., Stevens, M. C., et al. (2023). Unobtrusive Human Fall Detection System Using mmWave Radar and Data Driven Methods. IEEE Sensors Journal, 23(7), 7968–7976. https://doi.org/10.1109/jsen.2023.3245063

Shilaskar, S., Bhatlawande, S., Chavare, R., et al. (2023). Vision Based Fall Detection with BRISK Feature Descriptor. In: Proceedings of the 2023 Second International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT). https://doi.org/10.1109/iceeict56924.2023.10157061

Thakur, N., & Han, C. Y. (2021). A Study of Fall Detection in Assisted Living: Identifying and Improving the Optimal Machine Learning Method. Journal of Sensor and Actuator Networks, 10(3), 39. https://doi.org/10.3390/jsan10030039

Vallabh, P., Malekian, R., Ye, N., et al. (2016). Fall detection using machine learning algorithms. In: Proceedings of the 2016 24th International Conference on Software, Telecommunications and Computer Networks (SoftCOM). https://doi.org/10.1109/softcom.2016.7772142

Waheed, M., Afzal, H., & Mehmood, K. (2021). NT-FDS—A Noise Tolerant Fall Detection System Using Deep Learning on Wearable Devices. Sensors, 21(6), 2006. https://doi.org/10.3390/s21062006

Wang, P., Li, Q., Yin, P., et al. (2022). A convolution neural network approach for fall detection based on adaptive channel selection of UWB radar signals. Neural Computing and Applications, 35(22), 15967–15980. https://doi.org/10.1007/s00521-021-06795-w

Weng, S. F., Reps, J., Kai, J., et al. (2017). Can machine-learning improve cardiovascular risk prediction using routine clinical data? PLOS ONE, 12(4), e0174944. https://doi.org/10.1371/journal.pone.0174944

World Health Organisation. (n.d.). Available online: https://www.who.int/news-room/fact-sheets/detail/falls (accessed on 1 August 2024).

Wretborn, J., Wilhelms, D. B., & Ekelund, U. (2023). Emergency department crowding and mortality: an observational multicenter study in Sweden. Frontiers in Public Health, 11. https://doi.org/10.3389/fpubh.2023.1198188

Wu, L., Huang, C., Zhao, S., et al. (2023). Robust fall detection in video surveillance based on weakly supervised learning. Neural Networks, 163, 286–297. https://doi.org/10.1016/j.neunet.2023.03.042

Zaboli, A., Ausserhofer, D., Sibilio, S., et al. (2021). Triage assessment of transitory loss of consciousness in the emergency department—A retrospective observational study. Journal of Advanced Nursing, 78(5), 1337–1347. https://doi.org/10.1111/jan.15048

Zachariasse, J. M., van der Hagen, V., Seiger, N., et al. (2019). Performance of triage systems in emergency care: a systematic review and meta-analysis. BMJ Open, 9(5), e026471. https://doi.org/10.1136/bmjopen-2018-026471

Zhang, X., Ji, J., Wang, L., et al. (2022). Image-based fall detection in bus compartment scene. IET Image Processing, 17(4), 1181–1194. https://doi.org/10.1049/ipr2.12705

Zhao, Y., Zhu, W., Wei, P., et al. (2022). Classification of Zambian grasslands using random forest feature importance selection during the optimal phenological period. Ecological Indicators, 135, 108529. https://doi.org/10.1016/j.ecolind.2021.108529