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Risk predictions of hospital-acquired pressure injury in the intensive care unit based on a machine learning algorithm

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Abstract

Pressure injury (PI), or local damage to soft tissues and skin caused by prolonged pressure, remains controversial in the medical world. Patients in intensive care units (ICUs) were frequently reported to suffer PIs, with a heavy burden on their life and expenditures. Machine learning (ML) is a Section of artificial intelligence (AI) that has emerged in nursing practice and is increasingly used for diagnosis, complications, prognosis, and recurrence prediction. This study aims to investigate hospital-acquired PI (HAPI) risk predictions in ICU based on a ML algorithm by R programming language analysis. The former evidence was gathered through PRISMA guidelines. The logical analysis was applied via an R programming language. ML algorithms based on usage rate included logistic regression (LR), Random Forest (RF), Distributed tree (DT), Artificial neural networks (ANN), SVM (Support Vector Machine), Batch normalisation (BN), GB (Gradient Boosting), expectation–maximisation (EM), Adaptive Boosting (AdaBoost), and Extreme Gradient Boosting (XGBoost). Six cases were related to risk predictions of HAPI in the ICU based on an ML algorithm from seven obtained studies, and one study was associated with the Detection of PI risk. Also, the most estimated risksSerum Albumin, Lack of Activity, mechanical ventilation (MV), partial pressure of oxygen (PaO2), Surgery, Cardiovascular adequacy, ICU stay, Vasopressor, Consciousness, Skin integrity, Recovery Unit, insulin and oral antidiabetic (INS&OAD), Complete blood count (CBC), acute physiology and chronic health evaluation (APACHE) II score, Spontaneous bacterial peritonitis (SBP), Steroid, Demineralized Bone Matrix (DBM), Braden score, Faecal incontinence, Serum Creatinine (SCr) and age. In sum, HAPI prediction and PI risk detection are two significant areas for using ML in PI analysis. Also, the current data showed that the ML algorithm, including LR and RF, could be

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regarded as the practical platform for developing AI tools for diagnosing, prognosis, and treating PI in hospital units, especially ICU.

KEYWORDS

hospital-acquired, intensive care unit, machine learning, prediction, pressure injury

Key Messages

- ML algorithms based on usage rate included logistic regression (LR), Random Forest (RF), Distributed tree (DT), Artificial neural networks (ANN), SVM (Support Vector Machine), Batch normalisation (BN), GB (Gradient Boosting), expectation–maximisation (EM), Adaptive Boosting(AdaBoost), and Extreme Gradient Boosting (XGBoost).
- Six cases were related to risk predictions of HAPI in the ICU based on an ML algorithm from seven obtained studies, and one study was associated with the Detection of PI risk.
- Also, the most estimated risks of Serum Albumin, Lack of Activity, mechanical ventilation (MV), partial pressure of oxygen (PaO2), Surgery, Cardiovascular adequacy, ICU stay, Vasopressor, Consciousness, Skin integrity, Recovery Unit, insulin and oral antidiabetic (INS&OAD), Complete blood count (CBC), acute physiology and chronic health evaluation (APACHE) II score, Spontaneous bacterial peritonitis (SBP), Steroid, Demineralized Bone Matrix (DBM), Braden score, Faecal incontinence, Serum Creatinine (SCr) and age.
- In sum, HAPI prediction and PI risk detection are two significant areas for using ML in PI analysis.
- Also, the current data showed that the ML algorithm, including LR and RF, could be regarded as the practical platform for developing AI tools for diagnosing, prognosis, and treating PI in hospital units, especially ICU.

1 | INTRODUCTION

Pressure injury (PI), or local damage to soft tissues and skin caused by prolonged pressure, remains controversial in the medical world.[1] Patients in intensive care units (ICUs) were frequently reported to suffer PIs, with a heavy burden on their life and expenditures.[2] The burdensome consequences of PI, particularly those encountered in ICUs, make it imperative to identify the most relevant risk factors and implement etiological prevention.[3] PI prevention relies primarily on nurse observation and assessment. Moreover, evidence has shown that some risk assessment tools for PI, such as the Braden, Norton, and Waterlow scales, are not sufficiently accurate and reliable yet.[4]

Hospital-acquired PI (HAPI) is a localised skin and/or lower tissue injury during hospitalisation caused by concentrated pressure on a specific body area.[5] Additionally, the incidence of HAPI might be correlated with various factors such as elderly, immobility, perfusion, nutritional status, haematological measures, disease severity, and diabetes.[6] While HAPI is generally preventable, approximately 2.5 million people in the United States suffer from HAPI in acute care centers annually.[7] Also, HAPI could lead to prolonged hospitalisation, chronic wound, pain, infection, and even death.[8]

Machine learning (ML) is a section of AI that has emerged in nursing practice and is increasingly used for diagnosis, complications, prognosis, and recurrence prediction.[9] In contrast to conventional statistical models, ML can actively learn complex relationships between data, overriding the limitations of non-linearity and maintaining stability in high-dimensional datasets.[10] Moreover, because medical data surges, electronic health records (EHRs) include various data types.[11] ML offers a unique advantage in analysing unstructured data, such as pictures and other types of data.[12] however, Many ML studies have shown that several problems still exist related to model construction.[10] Despite the excellent performance of models on local datasets, many researchers have failed to consider their reproducibility in other clinical environments, limiting the further promotion of this powerful decision-support tool in clinical practice.[13] In a previous study,[14] ML was applied to PI management, but prediction tasks were not described in detail.

2 | RESEARCH QUESTIONS

The study aimed to answer the following research question:

- What are the risk predictions of HAPI in the ICU based on an ML algorithm by R programming language analysis?

2.1 | Aim

As a result of the current issue, an analysis of the advantages and disadvantages of the model construction process needs to be conducted to summarise ML applications for PI prediction. Therefore, this study aims to investigate the risk predictions of HAPI in the ICU based on an ML algorithm by R programming language analysis.

3 | METHODS

3.1 | Data selection

In the current study, to extract relevant studies, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyzes) guideline was used.[15] An extensive search was conducted on the PubMed and ISI databases via relevant keywords, including "intensive care unit", "bedsore", "pressure injury", and "machine learning", from November 1, 2022, to January 11, 2023. The search was conducted independently by two researchers. Boolean "AND" and "OR "operators were used to associate keywords. The cases written on hospital-acquired PI were included. Also, to prevent data loss, the references of extracted articles were searched, and 20 related articles were found. As the next step, articles on PI incidence in non-ICUs and cases are written before 2015 were excluded. Ultimately, seven studies were extracted.

3.2 | R programming language plot

To create plots, the authors applied the R Programming language. R is a programming language for statistical computing and graphics that the R Core Team and the R Foundation for Statistical Computing support. Developed by statisticians Ross Ihaka and Robert Gentleman, R is used by data miners, bioinformaticians, and statisticians to analyse data and create statistical software.[16]

3.2.1 | Sankey plot

Also, to analyse the technical uses of ML in PI management, the "Sankey plot" was illustrated. Directed arrows on the Sankey plot have a width proportional to the quantity visualised: an indicator twice as broad represents double the quantity. A flow diagram may show, for example, energy flow, materials flow, water flow, or costs flow. At least two nodes (processes) are always drawn in a Sankey chart to illustrate directed flow. As a result, the Sankey plot provides information about values, system structure, and distribution. Therefore, they are a great alternative to standard flow charts and bar charts.[17]

3.2.2 | Chord plot

A chord plot was illustrated to visualise the simultaneous application of ML algorithms. Chord plots show interrelationships between data radially around a circle. Also, the plot shows the connections between several entities (called nodes), with arcs connecting the nodes representing relationships between the nodes. Flow importance is proportional to the size of the arc. In biological studies, chord plots are applied to investigate cell functions such as gene expression.[18]

3.3 | Gephi

The Gephi software (V 0.10) investigated the relationship between ML and HAPI-related risks. The Gephi software is an open-source tool for analysing networks and graphs. The Gephi uses a 3D render engine to display large networks in real-time and speed up the exploration. A flexible and multi-task architecture makes working with complex data sets and producing valuable visual results possible.[19]

4 | RESULTS

4.1 | ML algorithm

ML algorithms based on usage rate included logistic regression (LR), Random Forest (RF), Distributed tree (DT), Artificial neural networks (ANN), SVM (Support Vector Machine), Batch normalisation (BN), GB (Gradient Boosting), expectation–maximisation (EM), Adaptive Boosting(AdaBoost), and Extreme Gradient Boosting (XGBoost) (Figures 1 and 2).

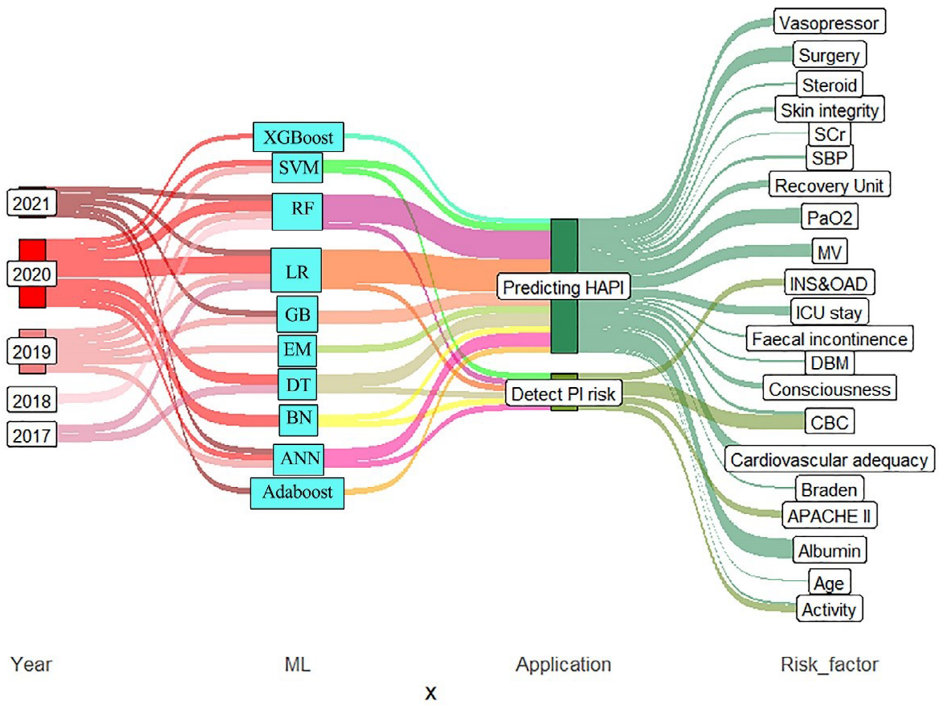

FIGURE 1 The "Sanky plot" of ML application in ICU-related PI.

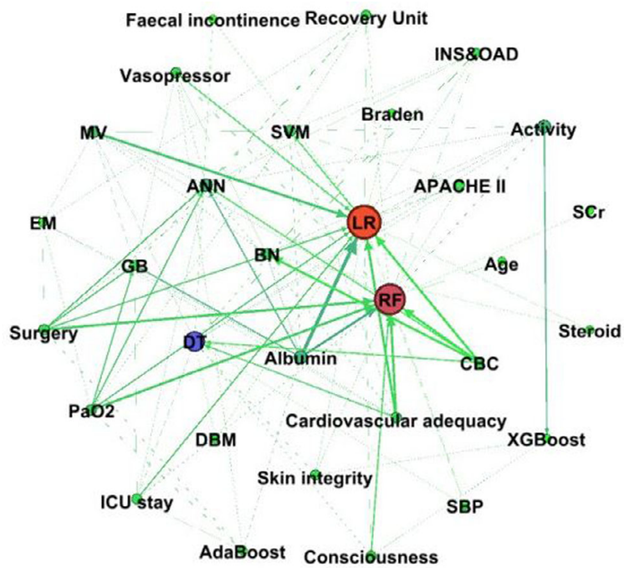

FIGURE 2 The relationship between ML and HAPI-related risks.

4.2 | Risk predictions of HAPI in the ICU based on an ML algorithm

Six cases were related to risk predictions of HAPI in the ICU based on an ML algorithm from seven obtained studies, and one study was associated with the Detection of PI risk. Also, the most estimated risks include Serum Albumin, Lack of Activity, mechanical ventilation (MV), partial pressure of oxygen (PaO2), Surgery, Cardiovascular adequacy, ICU stay, Vasopressor, Consciousness, Skin integrity, Recovery Unit, insulin and oral antidiabetic (INS&OAD), Complete blood count (CBC), acute physiology and chronic health evaluation (APACHE) II score, Spontaneous bacterial peritonitis (SBP), Steroid, Demineralized Bone Matrix (DBM), Braden score, Faecal incontinence, Serum Creatinine (SCr) and age (Figures 1 and 2).

4.3 | The simultaneous application of ML algorithms

According to the obtained data, The most simultaneous application of ML algorithms, including LR &RF, ANN &RF, ANN& LR, LR&DT, LR&SVM, and LR& BN (see Figure 3).

5 | DISCUSSION

The development of AI and computer technology has gradually spread ML across various disciplines. Additionally, in many studies, ML was used as a diagnostic tool. However, The application of ML across multiple nursing topics was less conducted and investigated. In the current study, by "R" analysis of the seven papers' results, we identified the most applied ML algorithm and the most critical risk factor for PI incidence, allowing us to develop high-quality predictive targets for future research.

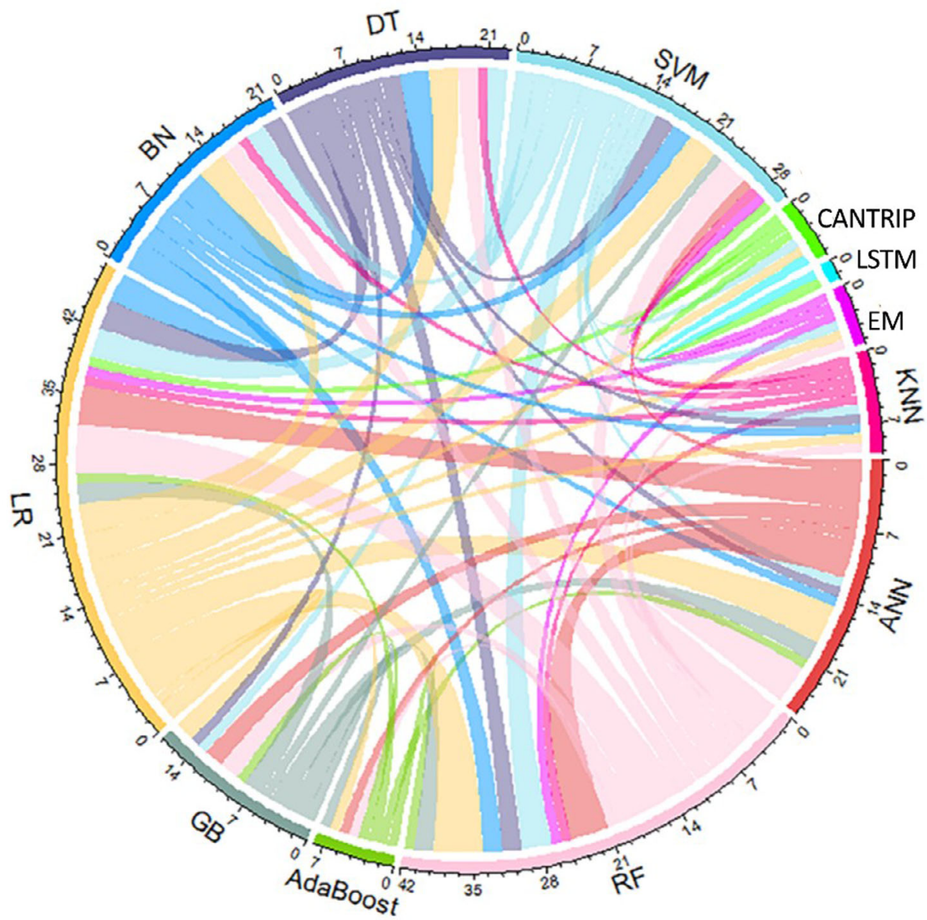

FIGURE 3 The "Chord plot" of ML applicated algorithms in ICU-related PI.

In the present study, obtained data showed that LR, RF, DT, and ANN are the most applied ML algorithm in ICU-acquired PI studies. Based on some dependent variables, LR is an ML classification algorithm that predicts certain classes. Essentially, the LR model sums the input features and calculates the logistic of the result.[20] In medical research, LR is applied for analysing binary and ordinal data.[21] Also, former studies have shown that LR can estimate the relative risks of rare events and evaluate the relative risk in cross-sectional and longitudinal studies, where the relative risk is not close to the odds ratio.[22] Additionally, Dweekat et al. indicated that LR is the most used approach in the analysis of HAPI.[23] Furthermore, in ensemble learning, RFs or random decision forests perform classification, regression, and other tasks by constructing many decision trees during training. Additionally, RF is used to perform classification tasks, where the output is the class selected by most trees. Moreover, RF corrects decision trees' habit of overfitting their training sets. When used for regression, they return the mean or average prediction of the individual trees. RF performs better than decision trees but is less accurate than gradient-boosted trees. However, data characteristics may influence their performance.[24] Based on former studies, RF algorithms are more precise than others in predicting comorbidities such as diabetes.[25,26] DT is an algorithm that searches values efficiently in a distributed manner. By working along multiple branches in parallel, DT can minimise the time spent searching for value in a tree-like data structure by combining the results of each component into one standard solution.[27] DT was also applied in investigating genomic, proteomics, and morality risk analysis.[28,29] As a result of their universal approximation capabilities and flexibility structure, ANNs are increasingly used to model and identify complex non-linear systems.[30] The architecture and function of the ANN are based on the structure and function of biological neural networks. ANN is also composed of neurons arranged in layers, like neurons in the brain.[31] Shining evidence has showed the advantage of ANN application in nursing care as a result of its superior ability to capture non-linear relationships.[32,33] Moreover, many documents indicate the application of ANN in nursing job analysis.[34]

According to chord plot data, the algorithms, including LR, RF, ANN, DT, SVM, and BN, are majorly applied together and, therefore, might be regarded as a proper algorithmic platform for developing AI-based tools for assessing PI risk and treatment. Additionally, medico-mathematic data showed that The complementary application of LR and FR algorithms has an appreciable predicting accuracy of (over 80%), making the method effective.[35] Also, based on former studies, ANN and RF algorithms could be an acceptable method for predicting healthcare disorders such as diabetes and fatty liver, indicating that the simultaneous application of the two algorithms can have sufficient accuracy.[36,37]

In the current study, the blood concentration of albumin is regarded as the most critical related factor for PI incidence. In ICU patients, hypoalbuminemia is defined as serum albumin levels below 3.3 g/dL.[38] Albumin is the most vital serum protein, and hepatosynthesis is the most important source of its production. The oncotic pressure is the essential function of albumin in the human body.[38] As a result of hypoalbuminemia, water from the blood moves into tissues, resulting in edema symptoms.[39] Edema is a major cause of pressure injuries as a result of the weakening of skin tissues that worsens with pressure or when the skin becomes ischemic or hypoxic, allowing the skin to damage easily.[40] Approximately 70% of ICU patients with hypoalbuminemia suffered pressure injuries.[40,41] PI prevention has long relied on repositioning and body activity. Laboratory studies have shown that the 90° lateral position decreases blood flow and transcutaneous oxygen tension close to anoxic (shallow oxygen levels) and increases interface pressure. Alternatively, this appears not to be the case when the patient is placed in a 30° lateral tilt position. In addition to preventing pneumonia, joint contractures, and urinary tract infections, body activity is crucial in preventing other complications associated with prolonged immobility.[29] In the present study, our data showed that ML could also measure the risk of PI by estimating physical activities. Interstingly, with the global spread of Covid-19, Studies have shown a significant prevalence of PI among Covid-19 patients receiving mechanical ventilation, which has led to an increase in mortality.[42] Accordingly, the present data indicated that lower PaO2 might be the second critical risk factor of PI incidence. Based on the evidence, lower PaO2 is directly associated with PI incidence through decreased PH.[43] Indeed, hypoxia and necrosis caused by insufficient oxygenation can considerably increase the risk of PI development.[44] Also, KARAYURT et al. have shown that the lower PaO2 in ICU significantly relates to PI occurrence.[45]

6 | LIMITATIONS

The present study is the first technical study on the application of ML in machine learning in the PI incidence of ICUs care unit. Accordingly, the existence of limitations in the study is unavoidable. First, only English-language published documents since 2015 were considered, which may have resulted in publication bias. Second, The review results may have been somewhat biased as a result of the overall poor quality assessment of the studies. Finally, the current study emphasises the technical application of ML in PI analysis, but valuable information could also exist in other fields, such as clinical.

6.1 | Recommendations for future research

According to the gathered data, the application of ML in PI management has promising opportunities. However, further development of the technology is still Required to qualify ML as a reliable assistant for managing PIs. In addition, the following suggestions can be considered research objectives for future studies;

- Development of an AI-based platform for approaches such as diagnosis, treatment, and wound care training.
- Identifying the most proper complementary algorithms to develop the ML-Based concept for ICU-related PI management.
- Development of visual-based tools for ICU-related PI management.

6.2 | Implications for clinical practice

Early diagnosis: ML algorithms can analyse large amounts of patient data to identify early signs of bedsores. Clinicians can intervene earlier and prevent bedsores from poor prognosis.

- Personalised treatment plans: ML can help clinicians develop personalised treatment plans based on a patient's unique medical history, physical condition, and other factors. This can improve the effectiveness of treatment and reduce the risk of complications.
- Resource allocation: By identifying patients at higher risk for bed sores, ML can help healthcare providers allocate resources more effectively, reducing the cost of care overall.
- Decision support: By analysing patient data, ML can provide clinicians with treatment recommendations that can improve patient outcomes.
- Quality improvement: To improve patient outcomes, data from patient records can be analysed using ML to identify trends and patterns in bedsores.

7 | CONCLUSION

In sum, the application of ML for PI analysis has gradually become a research target of interest in recent years. HAPI prediction and PI risk detection are two significant areas for using ML in PI analysis. Also, the current data showed that the ML algorithm, including LR and RF, could be regarded as the practical platform for developing AI tools for diagnosing, prognosis, and treating PI in hospital units, especially ICU. Nevertheless, data management, pre-processing, and model validation still required to be improved to build practical models that can be applied in clinical approaches.

AUTHOR CONTRIBUTIONS

All authors: idea for the review, study selection, data extraction, interpretation of results, writing of the manuscript. All authors read and approved the final manuscript.

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CONFLICT OF INTEREST STATEMENT

We do not have potential conflicts of interest with respect to the research, authorship, and publication of this article.

DATA AVAILABILITY STATEMENT

The datasets used during the current study are available from the corresponding author upon request.

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