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MDPI

Article

A Fused Multi-Channel Prediction Model of Pressure Injury for Adult Hospitalized Patients—The "EADB" Model

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Abstract: Background: Pressure injuries (PIs) are increasing worldwide, and there has been no significant improvement in preventing them. Traditional assessment tools are widely used to identify a patient at risk of developing a PI. This study aims to construct a novel fused multi-channel prediction model of PIs in adult hospitalized patients using machine learning algorithms (MLAs). Methods: A multi-phase quantitative approach involving a case–control experimental design was used. A first-hand dataset was collected retrospectively between March/2022 and August/2023 from the electronic medical records of three hospitals in Palestine. Results: The total number of patients was 49,500. A balanced dataset was utilized with a total number of 1110 patients (80% training and 20% testing). The models that were developed utilized eight MLAs, including linear regression and support vector regression (SVR), logistic regression (LR), random forest (RF), gradient boosting (GB), K-nearest neighbor (KNN), decision tree (DT), and extreme gradient boosting (XG boosting) and validated with five-fold cross-validation techniques. The best model was RF, for which the accuracy was 0.962, precision was 0.942, recall was 0.922, F1 was 0.931, area under curve (AUC) was 0.922, false positive rate (FPR) was 0.155, and true positive rate (TPR) was 0.782. Conclusions: The predictive factors were age, moisture, activity, length of stay (LOS), systolic blood pressure (BP), and albumin. A novel fused multi-channel prediction model of pressure injury was developed from different datasets.

Keywords: pressure injury; prediction model; machine learning

Academic Editors: Hazrat Ali and Kashif Ahmad

Received: 24 December 2024
Revised: 7 February 2025
Accepted: 14 February 2025
Published: 18 February 2025

Citation: Barghouthi, E.D.; Owda, A.Y.; Owda, M.; Asia, M. A Fused Multi-Channel Prediction Model of Pressure Injury for Adult Hospitalized Patients—The "EADB" Model. *AI* **2025**, *6*, 39. https://doi.org/10.3390/ai6020039

1. Introduction

Pressure injuries are increasing worldwide, and even if they are preventable, there has been no significant improvement in their prevention [1]. Hospital-acquired pressure injury (HAPI) among patients admitted to intensive care units (ICU) ranges from 14.3% to 43.2%, and in traumatic patients ranges from 20.3% to 38.5% [2]. Global prevalence ranges from 6% to 18.5% [1]. Moreover, the number of deaths related to pressure injuries increased from 13,700 in 1990 to 20,300 in 2017 [3]. The literature showed that 41% of patients developed a pressure injury that was unavoidable, and 59% were avoidable [4].

The pressure injury impacts patient outcomes, length of stay (LOS), burden costs, mortality, and readmission rates. This increases the healthcare cost of patients, and LOS increasing significantly, delaying the discharge of the patient to home [5].

Prolonged pressure causes changes in body position in people with normal movement and sensory feedback to prevent injury. On the other hand, persistent pressure can cause

tissue ischemia, damage, and necrosis when this feedback mechanism is compromised, which can result in pressure injuries. These injuries usually begin when the pressure from body weight presses against the skin covering bony parts, or when pressure from medical devices exceeds the threshold required for venous and arterial blood flow, causing local tissue hypoxia. Furthermore, reperfusion injury, which results from the resumption of blood flow following ischemia, can worsen injury by inducing oxidative stress and inflammation, especially after repeated cycles of ischemia–reperfusion, which are more harmful than continuous ischemia [6].

Due to the increased metabolic demands of muscles, this damage frequently advances deeper before impacting the skin, so early symptoms are generally a warning of more serious underlying damage. The failure in the local circulation when lying at an angle causes friction and shear, which exacerbates hypoxia. Furthermore, sweat or incontinence-related wetness increases the vulnerability of the skin to harm during repositioning, hence elevating the risk of pressure injuries [7].

The complexity of a pressure injury mainly refers to the multiple factors accompanying the affected patient and the treatment environment. In other words, a hospital-acquired pressure injury results from a dynamic process of nonlinear contributing factors from the care process and patient interaction [8].

The identification of risk factors for pressure injury enables the utilization of preventive measures at the proper time and before the occurrence of pressure injury [2]; various risk factors affect pressure injury, and some of them are predictor variables [9].

Those factors may include, but are not limited to, age, gender, body mass index, length of stay, medications, vital signs, anesthesia, Braden scale score, Braden subscale (sensory perception, moisture, activity, mobility, nutrition, and friction and shear) and diagnoses such as cancer, cardiovascular disease, diabetes mellitus (DM), renal failure, and respiratory issues [2,9–14]. Atherosclerosis, urgent admissions, paralysis, congestive heart failure, and procedures performed in the lower limbs or amputation posed as high-risk factors for pressure injuries [14]. Also, the most impactful risk factors for pressure injuries are anemia, hypoalbuminemia, and staff knowledge about the possible risk factors [11]. Also, falls, repositioning, and oxygen level [15]. Pressure injury correlates with knowledge about the healing process and its length after receiving effective treatment strategies [16].

Finally, some of the risk factors correlate with the period in which patients acquired a pressure injury. For example, patients with low levels of consciousness or ventilators acquired pressure injuries at an early stage of hospital stay, while sedative patients, patients in need of nutrition interventions, patients with a tracheostomy tube, patients suffering from diarrhea, patients on medications such as steroids, anticoagulants, anti-inflammatory, and patients with gastric tubes acquired pressure injuries at a late stage of their hospital stay [2].

Visual skin assessment (VSA) to predict pressure injury relies on assessment tools that cannot be reliable prediction methods [17], and these methods are limited and problematic because pressure injuries develop from the deep tissue, but they cannot be noticed until they reach the skin layer [18]. When this leads to an incidence of pressure injury, the patient will have already sustained a pressure injury by that time [17]. Thus, the method needs to be improved to detect pressure injury earlier through a different way to help healthcare providers set and implement prevention measures for pressure injury [18].

Objective measures to predict pressure injury called biomarkers, defined as the normal reaction to physiological skin irritation [17], have significant potential to identify the risks of pressure injury through identifying inflammation, activated by inflammation biomarkers such as keratinocytes before the skin changes and skin injury [19]. According to [17], which reviewed the role of the biomarkers in early detection, conducted without limitation for the

date of publication, language, and age of patients, biomarkers are used to detect pressure injury. The reviewed biomarkers included albumin, Waterlow score, hemoglobin (Hb), C-reactive protein (CRP), age, gender, heart-type fatty acid-binding protein (H-FABP), and granulocyte–macrophage colony-stimulating factor (GM-CSF). The combination of gender, age, Hb, Albumin, and CRP are the significant biomarkers, at 0.79.

One prediction model of pressure injury aimed to identify the predictive risk factors that impact pressure injury without relying on traditional assessment methods [20]. Furthermore, pressure injury risk factors are vast, and the staff cannot predict all cases or scenarios that lead to or cause pressure injury due to the uniqueness and variation in patients [8,10,21].

According to Sir William Osler, "medicine is a science of uncertainty and an art of probability". This evolution of a new approach to medicine indicates the importance of machine learning in the healthcare industry and formulates the promising future of artificial intelligence (AI) [22,23].

A flourishing advancement in technology has impacted the digitalization of the healthcare industry, increased the rapid progress of electronic medical records, and made electronic medical records mandatory [24]. Electronic medical records are used to keep medical information and provide healthcare providers with patient data; electronic medical record assist in transforming healthcare and traditional medical records [25].

The availability of electronic medical records enables the utilization of other benefits such as the efficiency of resources, supporting decision making, and improvement in the quality of care and the work–life balance of family physicians [24].

Based on the widespread utilization of electronic medical records, and in order to maximize their benefits, AI has been implemented in different categories of healthcare; this approach emerged in 1950, and since then, machine learning applications have been implemented in the healthcare industry [26].

The promising aspects of AI and its applications have been shown in different domains, such as the transformational role of machine learning as one of the vital usages, predicting the risks of events and disease, helping in the diagnosis of diseases, accuracy in therapeutic approaches, analysis of the complex data patterns, and enhancement of the quality of clinical trials [23,26–28].

Deep learning, AI, or machine learning are used interchangeably, aiming to acquire the machine intelligence of humans without programming [26]. Machine learning data are randomly distributed to the training, test, and validation sets to maintain reliability and eliminate prediction bias [29]. The learning methods are categorized into supervised, unsupervised, or semi-supervised, which are types utilized based on the research purposes and the research question; the supervised method is widely used to predict disease or risk, the unsupervised method is utilized to evaluate data by reduction, and the semi-supervised method is used to build a strategy from data [26].

Two studies, Assadi et al. [30] and Parashar et al. [31], were conducted to elaborate on the use of machine learning in the health industry and provide a proper direction for utilizing machine learning in the future. The studies revealed that machine learning might provide the interpretation and evaluation of diagnostic tests, transformation, the processing of electronic medical records, and a framework for electronic medical records. Also, the integration of the machine learning framework needs to be considered with the three dimensions of integration context: patients, users, and technical staff. Finally, the model design must be facilitated and guided by an engineering method in order to improve the model's success in the integration phase.

A systematic review study was conducted by Tofaffaha et al. [32] to review applications of AI and decision support systems (DSSs) that were used to reduce pressure injuries,

which revealed that there was insufficient evidence for the impact of AI on the prevention of pressure injuries, and most of the proposed solutions were not implemented in healthcare settings.

The diagnostic accuracy of machine learning was discussed in Lao et al. [33]'s systematic review and meta-analysis study, which was conducted to assess accuracy in the diagnosis of anterior cruciate ligament (ACL) injury; this study provided a significant protocol to utilize the prediction model of ACL injury based on magnetic reasoning imagery (MRI). According to Gefen's study [34], which highlights the absence of biomedical technology to assist in screening or identifying cell or tissue damage early, there is no technology to detect inflammation, damage, or poor perfusion for the affected area of a pressure injury.

To the best of the researchers' knowledge, this research is the first to construct a novel fused multi-channel prediction of pressure injury model for adult hospitalized patients. This research will provide an important implication for healthcare providers, mainly nursing staff, to identify the patients at risk of pressure injury during hospitalization and to consider the pressure injury risk factors and biomarkers for early detection.

This research is going to propose four questions: (1) Are the fused multi-channel machine learning-based prediction models identifying the patients at risk of pressure injury in hospitalized adult patients? (2) What is the best machine learning algorithm to predict pressure injury? (3) What is the best accuracy achieved? (4) What are the predictive factors that are utilized in the prediction model?

This paper is divided into seven sections: (1) an introduction, which provides the reader with background about the topic; (2) a literature review, which will summarize the previous work related to this topic; (3) Materials and Methods, which includes data collection, data processing, exploratory data analysis, feature engineering, machine learning algorithms used in the prediction models, and performance evaluation; (4) Results, including the risk factors and findings of the predictions models; (5) a discussion of the findings; (6) our conclusions and recommendations; and (7) the limitations of the study.

2. Literature Review

Several studies have presented data-driven models for predicting pressure injuries by utilizing various machine learning algorithms and techniques [8,21]. One prediction model of pressure injury aimed to identify the predictive risks factors that impact pressure injury without relying on traditional assessment methods [20]. Furthermore, pressure injury risk factors are vast, and the staff cannot predict all cases or scenarios that lead to or cause pressure injury due to the uniqueness and variation of patients [8,10,21].

Pressure injury affects patient outcomes and treatment plans. It may lead to serious complications before the staff can identify a pressure injury occurrence, so prediction methods for pressure injury identify it earlier and alarm the nurses and system of the risk of pressure injury for the admitted patients according to certain factors and biomarkers [8].

The current method of assessing pressure injury relies on skillful or qualified nurses to determine the risks of pressure injury. Unfortunately, the shortage of qualified specialized nurses is an ongoing problem [35], which leads health scientists, nursing leaders, and treating physicians to seek to apply a new methodology that is capable of identifying all risk factors and predicting pressure injury earlier, before the skin changes and the patient is harmed, in order to take necessary measures to prevent a hospital-acquired pressure injury and maintain patient safety [23,36].

Some of the literature discusses prediction models in an inpatient setting, such as Ladios-Martin et al. [20], who collected data from adult ICU inpatients, Do et al. [37], who collected data from adult hospitalized patients, Walther et al. [38], who collected data from

inpatients, Song et al. [39], who collected data from five hospitals, and other studies discuss prediction models in emergency settings, such as Wei et al. [40], who collect data from patients in emergency departments.

The utilization of machine learning to construct a prediction model for pressure injury is discussed in the literature, and prediction models for pressure injury have been developed. And yet, there are differences in the risk factors and biomarkers that have been discussed and included in the models.

The following studies showed the unique potential risk factors and biomarkers used in the developed models in each study, such as reason for admission and medical history which was studied by Xu et al. [41]; medications and ventilation, studied by Shui et al. [42]; admission weight, studied by Cramer et al. [43]; vasopressor medications, sedation, and oxygenation, studied by Alderden et al. [10]; Hb, and comorbidities, studied by Tang and Xu [44]; oral mucosal, endotracheal tube (ETT), vasopressor, and hematocrit (HCT) steroids were studied by Choi et al. [45]; severity of illness was studied by Anderson et al. [46]; diet, pain, paralysis, skin condition, comorbidities, and department type were studied by Nakagami et al. [21]; cancer, anti-cancer therapy, Waterlow score, acute physiology and chronic health evaluation (APACHE) II score, and blood purification were studied by Sun et al. [47]; place of birth and hospital type were studied by Ladios-Martin et al. [20]; and immunocompromised status was studied by Deschepper et al. [48].

The common risk factors and biomarkers used in most of developed models studies were age, gender, weight, diagnoses, length of stay, albumin, comorbidities, Braden scale, level of consciousness, incidence of pressure injury, clinical laboratory results, patients' demographics, diagnosis, body mass index, heart rate, mean arterial pressure, and temperature [8,10,20–22,36,38,39,41–54].

Machine learning and artificial intelligence have a promising future in predicting pressure injuries and assisting healthcare providers in detecting pressure injuries earlier. For example, Hyun et al. [51] developed a prediction model which used LR with nine features for patients in the ICU and compared it to their Barden scores, and the model showed an acceptable level of pressure injury prediction; the performance metrics are as follows: accuracy 91.7%, sensitivity 65%, specificity 69%, positive predictive value (PPV) 21%, negative predictive value (NPV) 34%, and area under the curve (AUC) 73%. Ji-Yu et al. [52] developed a prediction model (XGBoost) for patients undergoing cardiovascular operations, and the model predicted pressure injury based on the clinical data; the performance metrics of the prediction model were as follows: accuracy (0.80), sensitivity (0.81), specificity (1), PPV (1), NPV (0.76), and AUC (0.50–1). Ladios-Martin et al. [20] set up a prediction model (LR, SVR, RF, and DT) and seven features were included in the prediction model for patients in ICU, and the performance metrics of the prediction model were excellent, as follows: accuracy (0.65–0.68), sensitivity (0.90), specificity (0.74), precision (8.76–10.87), recall (0.99–1), and AUC (0.89). Hu et al. [50] developed three prediction models (DT, LR, and RF) for inpatients that predicted pressure injury and the performance metrics to measure the results of the experiments were as follows: sensitivity (0.69–1), specificity (0.721–0.99), precision (0.79–0.99), recall (0.82–1), and AUC (0.876–1); the RF was the best model.

The potential risk factors recruited by the developed prediction models in the previous literature ranged from 6 to 50 risk factors; the common risk factors were diseases, laboratory results, the Braden scale, use of medications, age, vital signs, gender, body mass index (BMI), LOS, duration of surgery, critical condition, Glasgow coma scale (GCS), weight, mechanical ventilation, anesthesia and sedation, oxygenation, history of PIs, and department type (open or closed unit). Dweekat, Lam, and McGrath's [55] study, which was the study with the highest number of risk factors, recruited them from the rest with 50 risk factors.

The most common research methods in the literature were cohort retrospective studies, which formulated 59% of the total studies, followed by cohort prospective studies, about 19%, and 7% experimental design. The datasets ranged between 206,540 patients and 149 patients, and the most common data balancing method was random oversampling, which comprised 34% of the developed models and was followed by synthetic minority oversampling at 14%. Furthermore, collecting data from the hospital's electronic medical records (EMRs) was the dominant approach at 74% of the total databases. Finally, the developed prediction models recruited their samples from hospital settings, and most hospital settings were intensive units, with 52% of total developed models, and 37% did not report the setting type or department type.

However, although the results obtained from these studies are promising, none of these studies successfully utilized a fused multi-channel prediction model of pressure injury. Furthermore, from the previous literature and based on the variables, features, performance metrics, and context discussed in these studies, this literature review of the previous work on prediction models of pressure injury has shown that the prediction model predicts which patients may develop pressure injury based on their risk factors but does not predict when the patients may acquire the pressure injury. Additionally, one of the gaps found in the previous works is that none of them studied, or investigated, the accreditation status as a variable or feature in the prediction model developed in those studies.

3. Materials and Methods

This section presents the methodology of the study and is divided into data collection, data preprocessing, feature engineering, and construction prediction model by using machine learning algorithms. Figure 1 illustrates the main phases of the prediction model of pressure injury. The next subsection will explain in detail these five phases and their components utilized in the construction of the pressure injury prediction model.

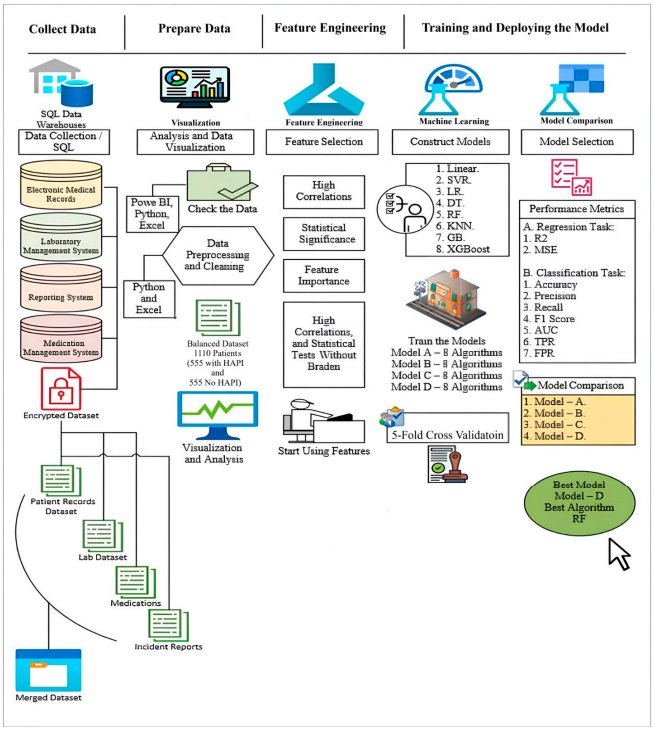

Figure 1. Method of construction for prediction model.

3.1. Data Collection

The researchers provided the information technology (IT) department with a list of all required predictable variable data with complete definitions of each item. These data were extracted from hospital databases by structured query language (SQL), and the researchers performed a quality check on the quality of the data extracted, and the missing or irrelevant data were corrected and changed; the final dataset met all requirements.

The study was conducted at a Private Hospitals Group called Arab Hospitals Group which included the following hospitals: Istishari Arab Hospital, Specialized Arab Hospital, and Ibn Sina Specialized Hospital (which are coded as RX, NX, and JX hospitals). These hospitals are private sector facilities located in the middle and north of the West Bank with a total bed count of 450 and total admissions of 42,500 patients annually [56].

The study population included a sample of patient medical records who were treated at three private hospitals in Palestine (RX hospital, NX hospital, and JX hospital). Hospital statistics showed that there were about 85,500 admissions annually for all three hospitals [57]. A first-hand dataset was collected retrospectively from the databases of the hospitals. These data were collected from the patients' electronic medical records and reporting system based on the inclusion and exclusion criteria. No participants or patients were required in this study. The inclusion criteria for the study included adult patients admitted to the hospitals, patients without pressure injuries on the day of admission, and patients screened on admission for pressure injury by the Braden scale. In addition, the study excluded patients younger than 18 and those admitted to the hospital with pressure injuries acquired from outside the hospital (home or other facilities before admission).

The data collected consisted of three datasets with an overall count of 1,900,132 rows and 45,990 patient records. The collection period included all data (census) according to the inclusion criteria from 1 March 2021 till 31 August 2023 retrospectively for the three hospitals as a primary data source (from the hospitals' database), which meant that the data were extracted by the IT staff based on the researchers' request and on the data extraction sheet for research purposes and first-hand dataset use.

Data confidentiality was maintained for all types of data, and confidentiality was assured for the hospitals, in that the data would not be available for anyone who was not involved in the study. The data were maintained in a secure file and a locked computer. Additionally, the patients' names, ID numbers, and dates of birth were not included in the data collection and were not required in the study. Finally, that data and information was utilized for research purposes only, and the researchers encrypted the hospital name through codes after mapping those codes with hospitals in the data collection process to maintain the privacy of the hospitals.

The data extracted included all the risk factors (age, gender, length of stay, diagnosis, department type (open units and intensive units), vital signs, anesthesia, mechanical ventilator, Braden score, Braden subscales (sensory perception, moisture, activity, mobility, nutrition, and friction and shear), biomarkers of pressure injury Hb, white blood cells (WBC), CRP, aspartate aminotransferase (AST), blood urea nitrogen (BUN), creatinine, hemoglobin A1c (HA1c), bilirubin, albumin (Alb), uric acid, and protein), and medication management system information (to extract all medications that were applied to patients during their hospital stays).

In addition, data of hospital-acquired pressure injury incidences were extracted from the incident management system retrospectively available in the three hospitals, including the stages of pressure injury (stage one, stage two, stage three, or stage four). All the extracted variables were linked together with a unique identifier number called (encounter ID) which was autogenerated by the system used by the three hospitals to facilitate the linking of the variables and datasets together.

3.2. Data Processing

The researchers extracted a balanced dataset with a total of 1110 patients (the total number of patients) with an overall count of 92,417 rows that included all patients with hospital-acquired pressure injury (555 patients) and a random sample of patients without hospital-acquired pressure injury (555 patients) via a simple random sampling technique from the original dataset which included 45,900 patients. This method was utilized to prevent the data size effect on the model's development and training of the algorithms.

After data collection, data preprocessing and cleaning was conducted. The data cleaning aimed to clean irrelevant and missing data. The data in the datasets were checked for duplication, which was linked with the unique number of each patient in these datasets; those steps were performed by the researchers using the Visual Studio program with assistance from the Python programming language. Those datasets were generated separately due to the nature of the data and their size (a dataset for laboratory tests, a dataset for medications, a dataset for patient records, and a dataset for incident reports). Those datasets were merged into one dataset, which included patient records with laboratory tests and medications.

The researchers used the Microsoft Excel and Python programming languages to perform data preprocessing and transformation to ensure that all columns' names were correct, and the content of the columns was clear to the reader. Furthermore, mapping of the hospitals with accreditation status and department categories was carried out.

The researchers performed data visualization which aimed to check the quality of the data and the effectiveness of the data cleaning and preprocessing; this phase showed some absence or errors in the data, which were brought back to the IT staff in order to fill in the missing data, and all issues were cleared. Phase two was carried out to understand the data, visualize all variables and features, and ensure that all the required data were well prepared. Phase three of the data visualization was performed to provide the researchers with a better understanding of the features that correlated with pressure injury, and the possible features that needed to be included in feature engineering.

3.3. Exploratory Data Analysis

The balanced dataset included 1110 patients, which included all patients with hospital-acquired pressure injury (555 patients), a random sample of patients without hospital-acquired pressure injury (555 patients), and an overall count of 92,417 rows. The total number of patients from the RX hospital was (475 patients; 43%), from the NX hospital (382 patients; 34%), and from the JX hospital (253 patients; 23%). Moreover, patients from the non-accredited hospitals (NX and JX) were (635 patients; 57.2%), and (475 patients; 42.8%) of the dataset were from the accredited hospital (RX).

3.3.1. Risk Factors

The risk factors in this study were age, gender, length of stay, department type, diagnosis, operation, anesthesia, vital signs, Braden score, Braden subscales, mechanical ventilator, and medications. All these risk factors were collected from the hospitals during the data collection process, and the datasets included all these features for all patients who were applicable.

The distribution of the potential risk factors according to the dataset collected in relation to the categorization of pressure injury is presented in Table 1. This table shows the potential risk factors split into (555) patients with hospital-acquired pressure injury and (555) patients without hospital-acquired pressure injury. Table 1 includes the number of patients, with percentages, according to hospital, gender, age, accreditation status,

department type, anesthesia type, performed operation, mechanical ventilator, Braden scale level, and pressure injury grade.

Table 1. Percentage of potential risk factors according to pressure injury status.

Risk Factor	Sub-Risk Factor	Frequency and Percentages		Total
		Non-HAPI	HAPI	
Hospital	RX	262 (55.2)%	213 (44.8)%	475
	JX	108 (22.7)%	145 (30.5)%	253
	NX	185 (38.9)%	197 (41.5)%	382
Gender	Female	237 (49.9)%	230 (48.4)%	467
	Male	318 (66.9)%	325 (68.4)%	643
Age	Adults (25–64 years)	366 (77.1)%	218 (45.9)%	584
	Elderly (65 years and over)	128 (26.9)%	306 (64.4)%	434
	Young Adult (18–24 years)	61 (12.8)%	31 (6.5)%	92
Accreditation Status	Accredited	262 (55.2)%	213 (44.8)%	475
	Non-Accredited	293 (61.7)%	342 (72)%	635
Department Type	Intensive Units	154 (32.4)%	302 (63.6)%	456
	Open Units	401 (84.4)%	253 (53.3)%	654
Anesthesia	General	169 (35.6)%	176 (37.1)%	345
	Local Anesthesia	109 (22.9)%	54 (11.4)%	163
	Spinal	15 (3.2)%	3 (0.6)%	18
	Sedation	3 (0.6)%	10 (2.1)%	13
	Combined Spinal Epidural	0 (0)%	1 (0.2)%	1
	Epidural	1 (0.2)%	0 (0)%	1
Performed Operation	No	258 (54.3)%	311 (65.5)%	569
	Yes	297 (62.5)%	244 (51.4)%	541
Braden Scale Level	High Risk	31 (6.5)%	441 (92.8)%	472
	Low Risk	524 (110.3)%	114 (24)%	638
Pressure Injury Grade	Grade 1	0 (0)%	179 (37.7)%	179
	Grade 2	2 (0.4)%	279 (58.7)%	281
	Grade 3	0 (0)%	97 (20.4)%	97
Mechanical Ventilators	No	536 (112.8)%	442 (93.1)%	978
	Yes	19 (4)%	113 (23.8)%	132

The data showed that the average age of the patients was 55 years (with an SD of 19.61). The patients' gender distribution showed that the number of female patients was 467, representing 42.1% of patients, and the number of male patients was 643, representing 57.9%.

The number patients admitted to the "open units" across all hospitals was 654, representing 58.9% of the total patients, and 456 patients we admitted to the "intensive units", representing 41.1%. The data categorized the patients who underwent operations by their number in each hospital, totaling 541 and representing 49.2% of total patients. The number of patients who underwent operations under anesthesia was 541, representing 49.2% of the total.

For the Braden scale, the data showed that the number of patients at a high risk level was 472, representing 42.5% of all patients across all hospitals, while the number of patients at a low risk level was 638, representing 57.5%. The number of patients on mechanical ventilators was 132, representing 11.9% of total patients.

Table 2 includes the means of vital signs, LOS, and operation duration per hospital, and the average of each variable. The average length of a patient's stay (LOS) was 6.5 days

(with an SD of 14.61); based on the table below, LOSs were high for the HAPI patient group in comparison with non-HAPI patient group among the three hospitals, with an average of 14.8 days and an SD of (1.15) for the HAPI group and an average of 2.7 days with an SD of (0.95) for the non-HAPI group.

Table 2. Distribution of potential risk factors according to pressure injury status.

Risk Factor	Hospital	Mean		Average
		Non-HAPI	HAPI	
LOS (days)	RX	3.2	13.6	7.8
	JX	3.3	14.9	9.9
	NX	1.6	15.9	8.9
Operation Duration (hours)	RX	1.2	2.2	1.6
	JX	1.3	2.4	1.9
	NX	0.4	1.1	0.8
Systolic BP (millimeters of mercury)	RX	123	118	120
	JX	123	123	123
	NX	119	120	120
Diastolic BP (millimeters of mercury)	RX	71	67	69
	JX	73	72	72
	NX	70	67	69
Temperature (centigrade)	RX	36.5	36.5	36.5
	JX	36.4	36.5	36.5
	NX	36.5	36.5	36.5
Pulse (beats per minute)	RX	73	76	74
	JX	68	71	70
	NX	73	70	72

For the operation period, the non-HAPI patient group was lower than the HAPI patient group; the average was 0.96 h with an SD of (0.49) for the non-HAPI group, and the average was 1.90 h with an SD of (0.70) for the HAPI patient group.

The patients' vital signs in the datasets were systolic blood pressure, diastolic blood pressure, temperature, and pulse. These vital signs were distributed as follows: the average systolic blood pressure was 120.6 with an SD of 18.32 (the maximum was 197 and the minimum 45), the average diastolic blood pressure was 69.5 with an SD of 12.01 (the maximum was 118 and the minimum 26), the average temperature was 36.4 with an SD of 0.31(the maximum was 40 and the minimum 33.7), and the average pulse was 72.3 with an SD of 14.39 (the maximum was 180 and the minimum 33).

3.3.2. Medications

The data showed that the number of unique medications applied to patients was 1151 medications; the total number of medication doses for all patients was 29,009. The distribution of these medications among the three hospitals was as follows: RX at 42.1%, NX at 34.8%, and JX at 23.1%.

The top ten medications among all the medications ordered, 6906, represented 23.8%, as follows: Nexium (1301 orders, 4.5%), Perfalgan (1169 orders, 4%), Fentanyl (658 orders, 2.3%), Furosemide (605 orders, 2.1%), Clexane (601 orders, 2.1%), Metoclopramide (531 orders, 1.8%), Meropenem (514 orders, 1.8%), Potassium Chloride (512 orders, 1.8%), Dexamethasone (508 orders, 1.8%), and Propofol (507 orders, 1.7%). The distribution of these medications among the three hospitals was as follows: RX at 42.1%, NX at 34.8%, and JX at 23.1%.

3.3.3. Biomarkers (Laboratory Tests)

The data showed that 12 unique laboratory tests were requested for the patients in the dataset, as follows: Hb, WBC, CRP, AST, BUN, creatinine, HA1c, bilirubin total (T), bilirubin direct (D), Alb, uric acid, and protein.

The number of tests in the dataset was 50,895 tests. Most of those tests were WBC and Hb tests (11,664 tests, 22.92% and 10,402 tests, 20.44%, respectively), followed by creatinine (8208 tests, 16.13%), BUN (4871 tests, 9.57%), CRP (4487 tests, 8.82%), AST (3267 tests, 6.42%), albumin (3207 tests, 6.30%), bilirubin total (1981 tests, 3.89%), bilirubin direct (1885 tests, 3.70%), HbA1c (367 tests, 0.72%), protein (301 tests, 0.59%), and uric acid (255 tests (0.50%).

The average laboratory results for the patients in the dataset were abnormal (above normal range or below normal range according to the hospital's criteria). This included the following tests: Alb was 2.98 (with an SD of 0.64), bilirubin (D) was 1.56 (with an SD of 3.81), bilirubin (T) was 2.33 (with an SD of 5.06), Bun was 31.31 (with an SD of 26.20), creatinine was 1.59 (with an SD of 1.55), CRP was 89.17 (with an SD of 83.83), Hb was 10.30 (with an SD of 2.15), protein was 5.91 (with an SD of 3.01), AST was 111.51 (with an SD of 600.32), Hb A1c was 7.25 (with an SD of 2.14), and WBC was 11.13 (with an SD of 5.73). Uric acid, which was 5.85 (with an SD of 3.14), was the exception and within the normal range, as presented in Table 3.

Table 3. Average laboratory test results with interpretation of results.

Tests Name	Average Result	Normal Range	Interpretation
Albumin (Alb)	2.98	3.5–5.2	Below Normal
Bilirubin (D)	1.56	0–0.2	Above Normal
Bilirubin (T)	2.33	0.2–1.2	Above Normal
Blood Urea Nitrogen (Bun)	31.13	6–20	Above Normal
Creatinine	1.59	0.7–1.2	Above Normal
C-Reactive Protein (CRP)	89.17	<5	Above Normal
Hb	10.30	12.0–14.0	Below Normal
Hemoglobin A1c (Hb A1c)	7.25	<5.7	Above Normal
Protein	5.91	6.4–8.3	Below Normal
Aspartate Aminotransferase (AST)	111.51	0–40	Above Normal
Uric Acid	5.85	3.4–7	Normal
White Blood Cells (WBC)	11.13	4–11	Above Normal
Albumin	2.98	3.5–5.2	Below Normal

3.3.4. Pressure Injury

The dataset showed the pressure injury status for patients across hospitals: the number of hospital-acquired pressure injuries at RX was 213 patients out of 475, comprising 44.8%; at JX, 145 patients out of 253, comprising 57.3%; and at NX, 197 patients out of 382, comprising 51.6%. The number of patients with no pressure injury at RX was 262 patients, JX was 108 patients, and NX was 185 patients.

The incidence rate of hospital-acquired pressure injuries was 1.21 per 100 patients. The incidence rate was calculated for each hospital based on the number of admitted patients and the number of hospital-acquired pressure injuries in each hospital. The incidence rate for the RX hospital was the lowest, at 1.05 per 100 patients, followed by NX at 1.13 per 100 patients, and the highest rate among the three hospitals was JX at 1.75 per 100 patients.

3.4. Feature Engineering

Feature engineering and selection were needed, as well as model selection. The researchers utilized the results of the visualization and analysis to determine or target the features that correlated with pressure injury. Those features were categorized into three

divisions (risk factors, biomarkers, and medications), and the researchers developed four different subgroups of features (variables) to be assigned in the proposed models.

The feature subgroups were split into four based on correlation with pressure injury, statistical significance, feature importance, and potential factors without the Braden scale, as follows: (1) group A (potential factors that had a high correlation with pressure injury), (2) group B (potential factors that had statistical significance with pressure injury), (3) group C (potential factors that had a high importance of features), and (4) group D (potential factors that had a high correlation with pressure injury without the Braden scale). Each group of features was used in one model and with eight different algorithms to determine the success of the predictive features in the model based on the performance metrics of those models and algorithms.

3.4.1. Correlations with Pressure Injury

Correlations were made between pressure injuries and the risk factors and biomarkers, and the correlations of the variables were categorized into numeric (continuous variables) and categorical variables: this categorization and the type of data yielded two different charts of correlation.

Correlation of Pressure Injury with Risk Factors

The datasets had 37 variables that may have correlated with pressure injury; the correlations were visually reconstructed by using tools that helped in identifying significant relationships and ensuring that the findings were both interpretable and accessible. These included heat maps for Pearson correlations among numeric variables, which offered a color-coded representation of the correlation strengths and suitable plots for displaying Cramér's V results.

Figure 2 shows a strong correlation between pressure injury and Braden score (−0.63); this correlation is presented in a negative direction because a lower Braden score indicates a high risk of pressure injury. This means there is a significant negative correlation found between the Braden Score and pressure injury, r (78) = −0.63, $p < 0.01$. This indicates that lower Braden Scores, which suggest higher risk, are associated with a higher occurrence of pressure injuries.

Furthermore, this heat map shows a moderate positive correlation between pressure injury and age (0.42), indicating that a patient's age being older was associated with an increased likelihood of pressure injuries. Finally, there was a moderate positive correlation between pressure injury and length of stay (0.41), r (78) = 0.42, $p < 0.01$, indicating that longer hospital stays were associated with an increased likelihood of pressure injuries.

Figure 3 presents the correlation of the categorical variables with laboratory tests. It shows that there was a strong correlation between pressure injury type and pressure injury grade (0.71), which relied on the fact that pressure injury grades result from pressure injury type. There was a strong association between pressure injury grade and department name, V = 0.66, indicating a significant variability of pressure injury grades across different departments. A considerable association was also observed between pressure injury grade and diagnosis, V = 0.57, suggesting that the nature of the diagnosis significantly affected the grading of pressure injuries. Another notable association existed between pressure injury grade and the anesthesia type, V = 0.71, indicating that the type of anesthesia used may have influenced the severity grade of pressure injuries.

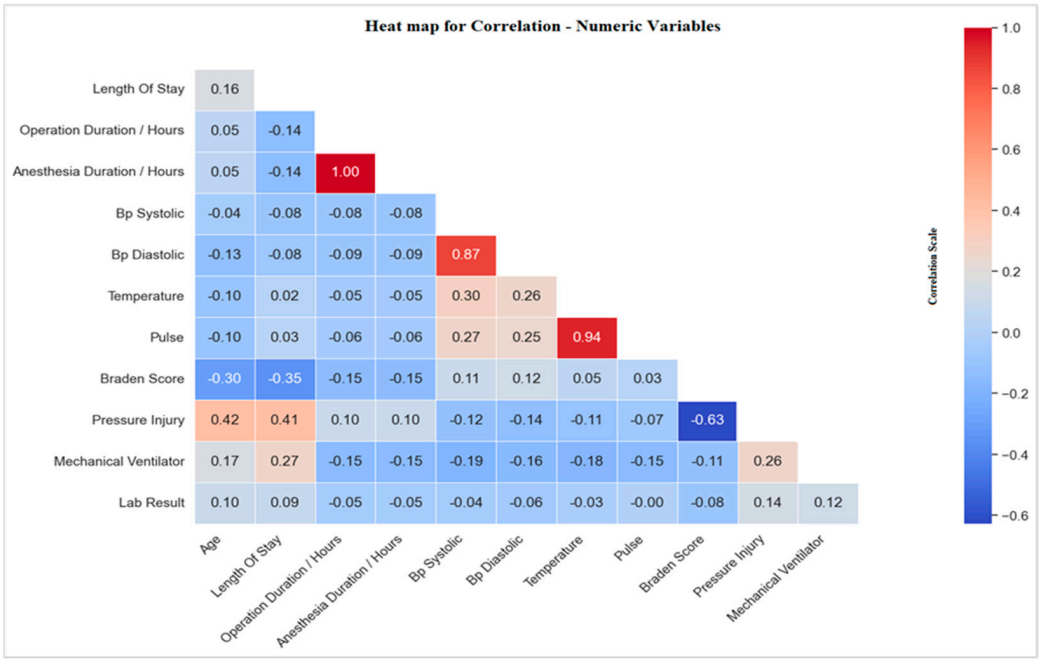

Figure 2. Heat map of correlations for numeric variables.

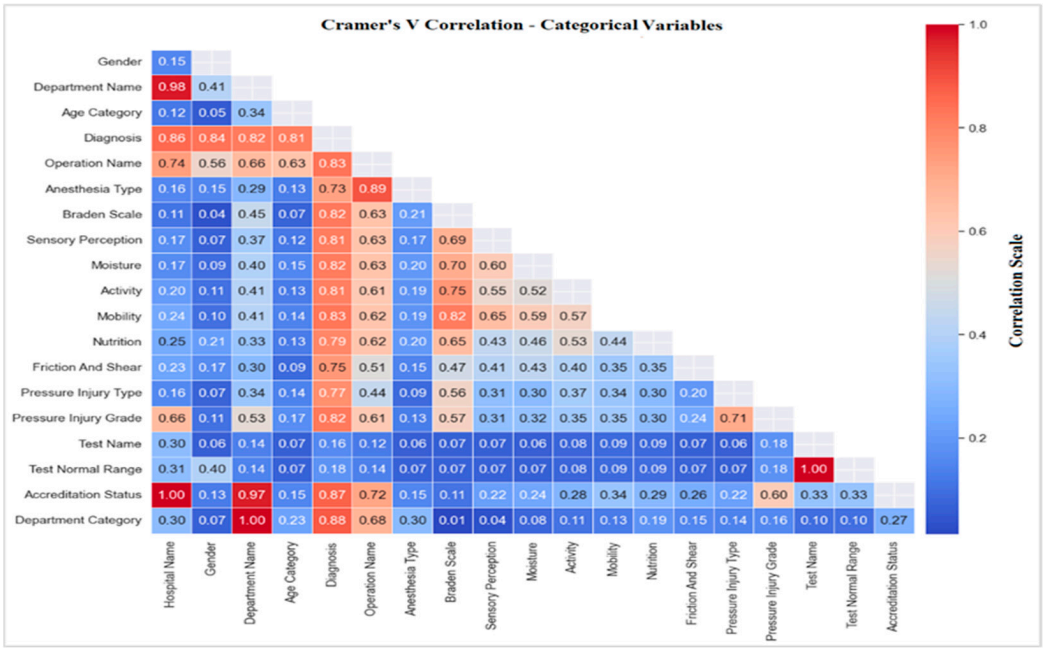

Figure 3. Cramer's V correlation for categorical variables with laboratory test results.

Figure 4 presents that there was a moderate positive correlation between medication and (pressure injury type and the Braden scale) (0.44, 0.49), which may relate to the type of medications used in the treatment or to reduce the risks of pressure injury; this also means that medication may correlate or lead to pressure injury.

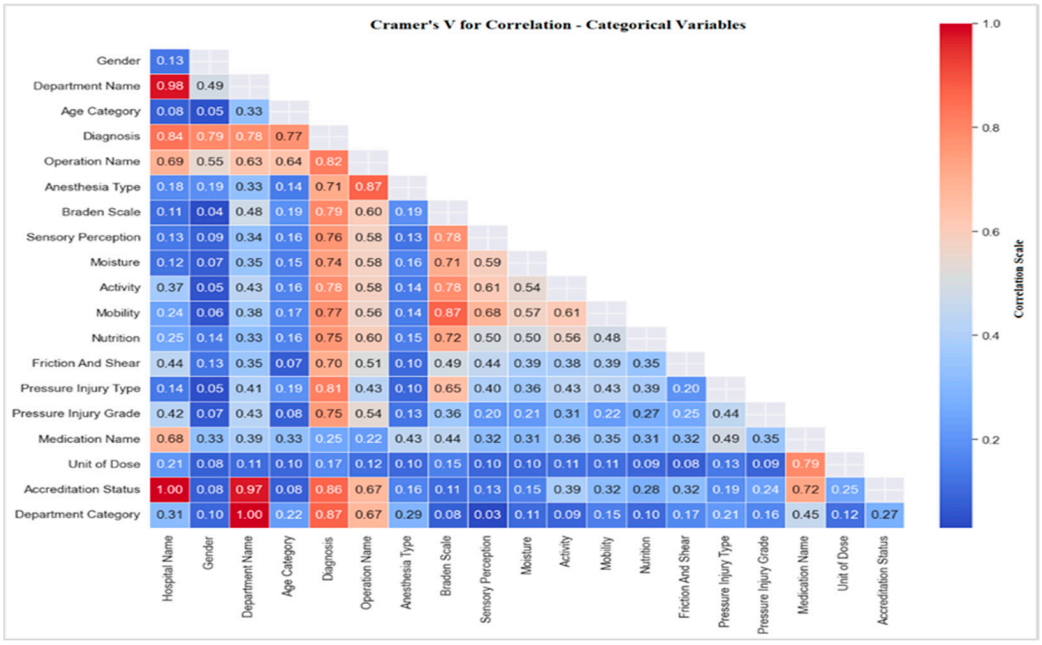

Figure 4. Cramer's V correlation for categorical variables with medications.

Correlation of Pressure Injury with Biomarkers (Laboratory Tests)

The data concerning laboratory tests and pressure injury showed that there was a weak negative correlation between pressure injury and laboratory test results (−0.06), which may be explained by the correlation of the results of laboratory tests with pressure injury being above or below the normal range for each test. In addition, some laboratory tests had high values in relation to the clinical situation. There were different factors, such as severity or the critical status of patient's condition, that impacted and affected the laboratory results significantly, as presented in Figure 5.

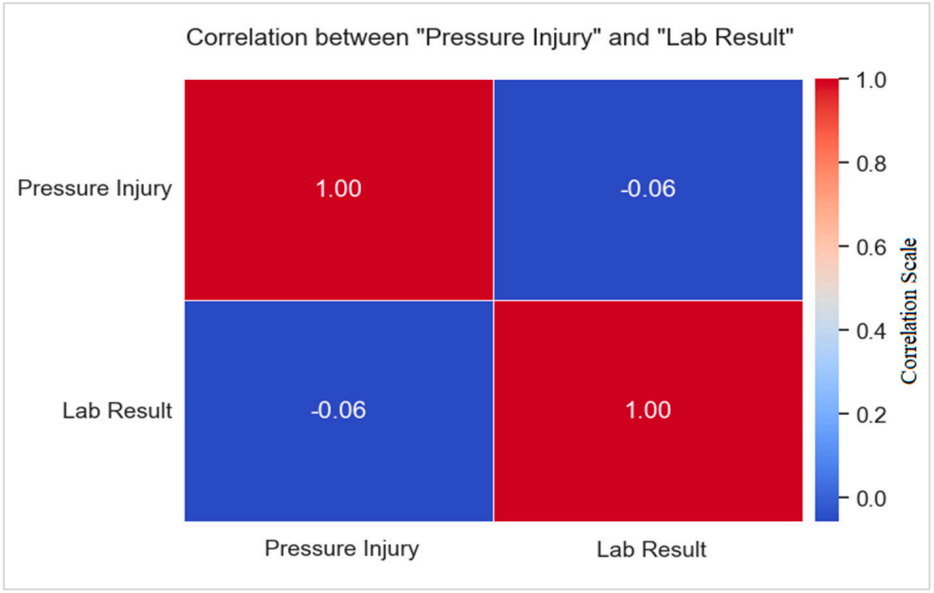

Figure 5. Correlation between pressure injury and lab results.

The data show that there was a strong negative correlation between pressure injury and Alb, which was (−0.90). There was also a moderate negative correlation between pressure injury and protein, which was (−0.51). The correlation between pressure injury and bilirubin (T) was (−0.39), and the correlation between pressure injury and bilirubin (D)

was (−0.38). Moreover, there was a strong positive correlation between pressure injury and WBC, which was (0.71). Finally, there was a weak positive correlation between pressure injury and creatinine, which was (0.32), and there was a weak positive correlation between pressure injury and CRP, which was (0.25).

The correlation analysis between pressure injury incidence and the laboratory results was conducted using Pearson's correlation coefficient. The analysis revealed a very weak, negative correlation between pressure injury and lab results, r = −0.06. This suggests that there was no significant linear relationship between the incidence of pressure injuries and the laboratory results.

3.4.2. Statistical Tests

In preparation for applying the *t*-test and ANOVA to compare means among the groups, and the Chi-Squared test to explore the association between two categorical variables, the key assumptions were verified to uphold the tests' validity.

Statistical Test of Pressure Injury with Biomarkers (Laboratory Tests)

The independent sample *t*-test was used to test the hypothesis of the biomarkers' (laboratory test) correlation with pressure injury. However, there were no statistically significant differences in the means of HbA1c related to pressure injury at the level ($p \leq 0.05$), where the *p*-value was equal (0.782), as presented in Table 4.

Table 4. Laboratory results according to pressure injury status (*t*-test).

Biomarkers	Condition	Mean	t	df	*p* Value	95% CI
Creatinine	Yes (HAPI) No (HAPI)	1.68 1.34	8.96	3989	<0.001	[0.26, 0.41]
CRP	Yes (HAPI) No (HAPI)	94.77 71.11	8.42	2150	<0.001	[17.18, 28.33]
WBC	Yes (HAPI) No (HAPI)	11.59 9.94	14.85	6666	<0.001	[1.43, 1.86]
Hb	Yes (HAPI) No (HAPI)	9.92 11.23	−26.58	4647	<0.001	[−1.41, −1.21]
BUN	Yes (HAPI) No (HAPI)	35.61 22.74	18.79	4385	<0.001	[10.89, 13.53]
AST	Yes (HAPI) No (HAPI)	118.30 132.53	−0.48	1231	<0.001	[−83.94, 25.57]
Alb	Yes (HAPI) No (HAPI)	2.86 3.28	−17.26	1639	<0.001	[−0.47, −0.37]
Bilirubin (T)	Yes (HAPI) No (HAPI)	2.11 2.77	−2.47	1022	<0.001	[−1.18, −0.13]
Bilirubin (D)	Yes (HAPI) No (HAPI)	1.36 1.96	−2.88	931	<0.001	[−1.01, −0.19]
Uric Acid	Yes (HAPI) No (HAPI)	6.37 5.27	2.91	226	0.20	[0.35, 1.85]
Hb A1c	Yes (HAPI) No (HAPI)	7.28 7.22	0.28	348	0.78	[−0.38, 0.51]
Protein	Yes (HAPI) No (HAPI)	5.81 6.14	−1.14	291	<0.001	[−0.83, 0.22]

Abbreviations: df: degree of freedom; CI: confidence interval; HAPI: hospital-acquired pressure injury; CRP: C-reactive protein; WBC: white blood cells; Hb: hemoglobin; BUN: blood urea nitrogen; AST: aspartate aminotransferase; Alb: albumin; T: total; D: direct; Hb A1c: hemoglobin A1c.

There were statistically significant differences between the means (creatinine, CRP, WBC, Hb, BUN, AST, Alb, bilirubin (T), bilirubin (D), uric acid, and protein) related to pressure injury at the level of ($p \leq 0.05$), with *p*-values equal to (1.61×10^{-16}, 2.43×10^{-40},

2.75×10^{-48}, 8.54×10^{-148}, 2.13×10^{-49}, 7.38×10^{-6}, 2.01×10^{-60}, 3.65×10^{-11}, 1.17×10^{-12}, 2.04×10^{-2}, and 1.51×10^{-4}) respectively, as presented in Table 4.

Statistical Test of Pressure Injury with Risk Factors

ANOVA was used for the continuous variables and for more than two categories, and included age, LOS, age category, type of anesthesia, operation duration, anesthesia duration, systolic and diastolic BP, temperature, pulse, pressure injury grade, Braden score, and Braden subscales (perception, moisture, activity mobility, and nutrition). There were significant differences between the means of age and age category relating to pressure injury at the level ($p \leq 0.05$), with p-values < 0.001. There were significant differences between the means of LOS relating to pressure injury at the level ($p \leq 0.05$), with p-values < 0.001. There were significant differences between the means of systolic BP, diastolic BP, temperature, and pulse relating to pressure injury at the level ($p \leq 0.05$), with p-values of (0.001, <0.001, 0.001, 0.040), respectively. There were significant differences between the means of anesthesia type and anesthesia duration with pressure injury at the level ($p \leq 0.05$), with the p-values (0.005 and <0.001), respectively. There were significant differences between the means of the Braden score and Braden subscales (perception, moisture, activity mobility, and nutrition) relating to pressure injury at the level ($p \leq 0.05$), with p-values (<0.001, <0.001, <0.001, <0.001, <0.001, <0.001, and <0.001), respectively. There were significant differences between the means of operation duration relating to pressure injury at the level ($p \leq 0.05$), with a p-value < 0.001. There were significant differences between the means of pressure injury grade relating to pressure injury at the level ($p \leq 0.05$), with a p-value < 0.001.

The Chi-Squared test was used for the categorical variables, which included gender, department type, performed operation, Braden scale, mechanical ventilator, accreditation status, pressure injury type, and medications. For the gender variable, there was no significant relationship between gender and pressure injury status at X2 (1, N = 1110) = 1.81, p-value = 0.670. In the department type variable, there was a significant relationship between pressure injury type and pressure injury status at X2 (1, N = 1110) = 81.527, p-value < 0.001. For the performed operation variable, there was a significant relationship between performed operation and pressure injury status at X2 (1, N = 1110) = 10.129, p-value = 0.001. For the Braden scale variable, there was a significant relationship between the Braden scale and pressure injury status at X2 (1, N = 1110) = 619.624, p-value < 0.001. In the mechanical ventilators variable, there was a significant relationship between mechanical ventilators and pressure injury status at X2 (1, N = 1110) = 75.974, p-value < 0.001. For the accreditation status variable, there was a significant relationship between accreditation status and pressure injury status at X2 (1, N = 1110) = 8.836, p-value = 0.003. For the pressure injury type variable, there was a significant relationship between pressure injury type and pressure injury status at X2 (1, N = 1110) = 1102.029, p-value < 0.001. Finally, for the medications variable, there was a significant relationship between medications and pressure injury status at X2 (1, N = 1151) = 6854.12, p-value < 0.001.

3.5. Constructing Models by Using Machine Learning Algorithms

Supervised machine learning was utilized, where the algorithms learned from the seen dataset with the title of the features. Then, testing was performed on the unseen data (testing dataset), in which the data had the same structure as the original dataset and the same features, and the algorithms could predict correctly [31].

The data were randomly assigned into three sets: training, test, and validation, with a ratio of (80% training and 20% testing). Moreover, the model's design was proposed and developed. This experiment was repeated to generate four models, and each model used one of the feature subgroups in the proposed model. Each model was a new experiment

and was identified with a unique number that was linked to one of the subgroup features. Each new model was trained with selected subgroup features and predictive modeling approaches in the Python program software (Version 3).

The researchers used eight algorithms of predictive modeling approaches that were categorized into two types: regression algorithms and classification algorithms. Each type had unique algorithms that could be utilized in the predictive model. The algorithms were popular in prediction, and the classification referred to the dependent variable. The target of the prediction was categorical (HAPI or No HAPI), and regression was used to predict the output of the model [58].

The machine learning algorithms used in the prediction models included (1) linear regression, (2) support vector regression (SVR), (3) logistic regression (LR), (4) random forest (RF), (5) gradient boosting (GB), (6) K-Nearest Neighbors (KNN), (7) decision tree (DT), and (8) extreme gradient boosting (XG boost). These algorithms were part of a complete set that could be used from a library of machine learning, which consisted of ten major approaches, and each approach consisted of multiple algorithms. These algorithms determined the way to deal with the data in the model and how the process of learning from the data was achieved to accomplish the model [58].

In each experiment, the model was trained, and the eight algorithms generated results from the training based on performance metrics; these metrics were divided into two types: classification and regression. For regression, the performance metrics were mean squared error (MSE) and coefficient of determination (R2); for classification accuracy, they were recall, precision, F1 score, the AUC, true positive rate (TPR), and false positive rate (FPR). The trained models were validated through a common technique called five-fold cross-validation. All the results of the models were validated.

Due to the size of the dataset used in this study, we recognize that there is a risk of overfitting, which could result in overly optimistic performance metrics. To ensure that the reported accuracy and F1 scores reflected the model's true predictive capability rather than its ability to overfit to the training dataset, we used feature selection and regularization techniques to further prevent the model from memorizing noise in the training data, as well as five-fold cross-validation during model development, which ensured that the model's performance was evaluated across multiple subsets of the data, thereby reducing the likelihood of overfitting by providing a more credible estimate of the model's generalizability.

Hyperparameter tuning was performed to optimize the performance of each machine learning algorithm. The goal was to identify the best combination of hyperparameters that maximized the models' generalization ability on unseen data.

For each algorithm, the specific hyperparameters and their ranges were as follows: linear regression: no hyperparameters to tune (default implementation); LR: regularization parameter (C), solver, and penalty; RF: number of trees (n_estimators), maximum depth of trees (max_depth), and minimum samples per leaf (min_samples_leaf); GB: learning rate, number of boosting stages (n_estimators), and maximum depth of trees (max_depth); SVR: regularization parameter (C), kernel type, and kernel coefficient (gamma); KNN: number of neighbors (n_neighbors), distance metric, and weight function; DT: maximum depth of trees (max_depth), minimum samples per leaf (min_samples_leaf), and criterion; XGBoost: learning rate, number of boosting stages (n_estimators), and maximum depth of trees (max_depth).

The performance of each hyperparameter combination was evaluated using five-fold cross-validation with accuracy as the primary metric. The combination yielding the highest average accuracy across folds was selected as the optimal configuration. Cross-validation was used to assess the generalization performance of the models and to mitigate overfitting.

By partitioning the dataset into five folds, we ensured that each fold was used exactly once as a validation set while the remaining folds were used for training.

The dataset was randomly split into five folds of equal size. For each fold, the model was trained on four folds and validated on the remaining fold. This process was repeated five times, with each fold serving as the validation set once. The performance metrics (e.g., accuracy, precision, recall) were averaged across all folds to obtain a robust estimate of model performance.

The different models were trained after the treatment and modified based on the results. Furthermore, the best models were applied again to save in another folder. The same dataset with the same data structure and features was reuploaded again to test the prediction models, and these models were compared based on the performance metrics; finally, the best model was selected based on performance metrics, and the success model was named by the "EADB Model" by the researchers, as presented in Figure 6.

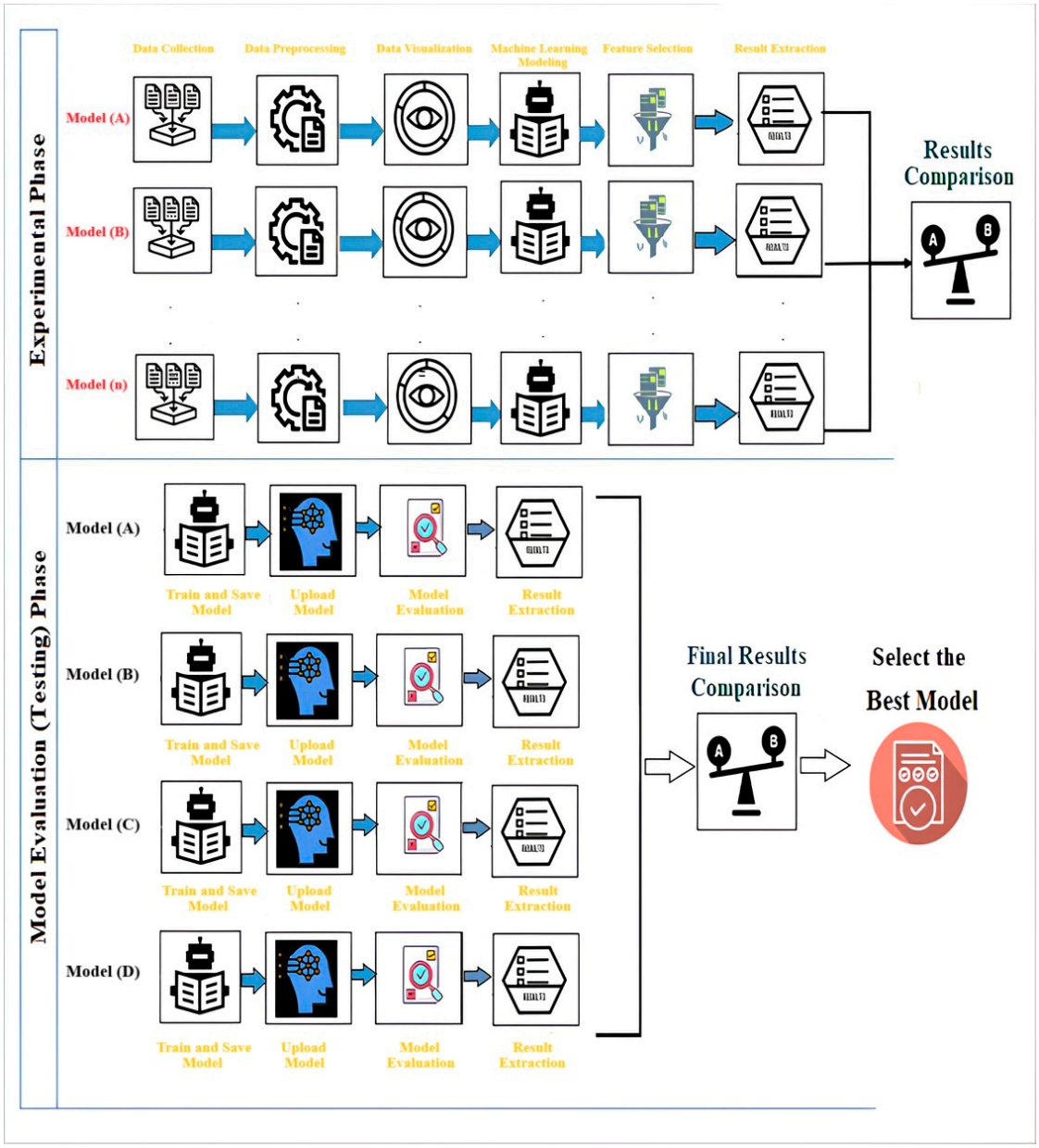

Figure 6. Model result extraction methodology.

- Linear regression was used to predict the dependent (y) from the independent (X) variables, and this prediction assumes that the two variables have an association such as a linear association [59].
- SVR was identified as part of the regression techniques and was considered a supervised learning algorithm. SVR can be predicted from training and test datasets, and its aim is to identify a function that is as flat as possible while also matching all the training data. It works to find the fit line and decrease the error or gap between the predicted and actual value [60].
- LR was utilized, which compares the data to a logistic function; it makes predictions about the chance that an incidence will occur, and the results fall between 0 and 1 [58].
- DT is a flowchart-like tree; each branch in the tree is considered a rule, and each leaf is considered an outcome for each rule. This algorithm works by selecting the best feature or attribute from all available features and considering the results of maximum information. This algorithm did not rely on a straightforward formula, and each path from the root to the leaf represents a DT. The paths classify the new entry or instance determined previously and based on the feature values in the original tree until the leaf node is built [61].
- RF was one of the classification algorithms and can be used for regression tasks. This algorithm works similarly to the DT algorithm and generates many trees in the training phase and testing phase, which results in stable results; for this reason, RF was also used in cross-validation. No equation was used in regression [61]. Its purpose is to construct a model that uses basic decision rules deduced from data attributes to forecast the value of a target variable. It divides the data according to specified criteria; there is no set formula for this, but instead, metrics, such as information gain [62].
- KNN is a basic instance-based learning method. A new instance is categorized using similarity metrics (such as distance functions). A query point is allocated to the data class with the greatest number of representatives among its nearest neighbors, and classification is determined by a simple majority vote of each point nearest neighbors [63].
- GB is an ensemble technique where new models are created, which predict the residuals or errors of prior models, and then added together in a stage-wise fashion. It combines the weak learners and creates a strong predictive model and is used to minimize errors for the new model; "boosting" means that each model corrects the errors of the previous model, the key idea is to set the target outcomes for this new model to minimize the loss function [64].
- XGBoost is an efficient implementation of a gradient-boosting framework. This algorithm uses a GB framework at the core but is optimized for speed and performance. Like GB, it involves creating new models that predict the residuals of prior models. It has unique features like handling missing data, regularization to avoid overfitting, and tree pruning [65].

3.6. Perfromance Evaluation

The performance evaluation included three types of evaluation: (1) performance metrics, (2) confidence intervals, and (3) significance tests. The performance metrics accuracy, precision, recall, F1 score, AUC, FPR, and TPR were utilized to measure the performance of each experiment to develop and to compare the performances of the developed models. In addition, a confusion matrix for TPR and FPR was used to compare the predictive values with the targeted values in this research, in order to test the performance of the prediction models [66–68] as presented in Table 5.

Table 5. Performance metric equations.

Metrics Name	Equations
True Positive Rate/Recall (TPR)	TPR = TP/(TP + FN)
False Positive Rate (FPR)	FPR = FP/(TN + FP)
Precision	Precision = TP/(TP + FP)
F-measure (F1 score)	F1 score = $2/(\text{Recall}^{-1} + \text{Precision}^{-1})$
Area Under the Curve (AUC)	AUC = ½. $\sum i^{n} = 1$ (fi + 1 − fi). (ti + 1 + ti)
Accuracy	Accuracy = TP + TN/(TP + TN + FP + FN)
Mean Square Error (MSE)	MSE = $1/n \sum (y - y)^2$ Best Value = 0, Worst Value = +∞
R-Squared	$R^2 = 1 - (SSE/SS_{yy})$ Where SSE = $\sum (y - y^{\wedge})^2$ $SS_{yy} = \sum (y - y^{-})^2$ Best Value = +1, Worst Value = −∞

Finally, significance tests were utilized to determine whether the observed differences in performance metrics were statistically significant. We performed the following tests: (a) Wilcoxon Signed-Rank Test: A non-parametric test used to compare two algorithms on the same dataset(s). This test was chosen because it does not assume normality and is robust to small sample sizes. (b) Friedman Test: A non-parametric test used to compare more than two algorithms across multiple datasets or cross-validation folds. If the Friedman test indicated significant differences, we performed a post hoc Nemenyi test to identify which specific pairs of algorithms differed.

Table 6 illustrates the confusion matrix with the actual and predicted probabilities. It shows that the matrix has four probabilities, which may be true positive (TP), false positive (FP), false negative (FN), and true negative (TN), in addition to the equation used in the prediction model and the metrics equation, with the meanings of the symbols used in those equations staying the same [58].

Table 6. Confusion matrix.

	Predicted—Positive	Predicted—Negative
Actual—Positive	True Positive (TP)	False Negative (FN)
Actual—Negative	False Positive (FP)	True Negative (TN)

4. Results

This section presents the experimental results of the prediction models for pressure injury, identifies the distribution of the risk factors into the training and testing datasets, and presents the developed models' findings.

4.1. Risk Factors Training and Testing Distribution

The risk factors for the prediction models of pressure injury were distributed into the training and testing datasets, as presented in Table 7.

Table 7. Risk factor distribution into training and testing datasets.

Factors/Features	Sub-Factors/Features	Training Dataset	Testing Dataset
Accreditation Status	Accredited	359 patients (75.6%)	116 patients (24.4%)
	Not Accredited	499 patients (78.6%)	136 patients (21.4%)
Department Category	Open Units	516 patients (87.9%)	138 patients (21.1%)
	Intensive Units	342 patients (73.5%)	114 patients (26.5%)
Gender	Male	501 patients (77.9%)	142 patients (22.1%)
	Female	357 patients (76.4%)	110 patients (23.4%)
Age Category	Elderly (65 years and over)	330 patients (76.0%)	104 patients (24.0%)
	Adults (25–64 years)	459 patients (78.6%)	125 patients (21.4%)
	Young Adult (18–24 years)	69 patients (75.0%)	23 patients (25.0%)
Performed Operation	Yes	415 patients (76.7%)	126 patients (23.4%)
	No	443 patients (77.9%)	126 patients (22.1%)
Anesthesia Type	General	256 patients (74.2%)	89 patients (25.8%)
	Local Anesthesia	134 patients (82.2%)	29 patients (17.8%)
	Spinal	13 patients (0.50%)	5 patients (0.77%)
	Sedation	11 patients (0.42%)	2 patients (0.31%)
	Epidural	1 patient (0.04%)	0 patients (0.00%)
	CSE	0 patients (0.00%)	1 patient (0.15%)
Mechanical Ventilator	No	762 patients (29.42%)	216 patients (33.33%)
	Yes	96 patients (3.71%)	36 patients (5.56%)
Braden Scale Level	Low Risk	500 patients (19.31%)	138 patients (21.30%)
	High Risk	358 patients (13.82%)	114 patients (17.59%)
Subscale/Moisture	Rarely Moist	393 patients (15.17%)	117 patients (18.06%)
	Occasionally Moist	348 patients (13.44%)	102 patients (15.74%)
	Constantly Moist	54 patients (2.08%)	12 patients (1.85%)
	Very Moist	63 patients (2.43%)	21 patients (3.24%)
Subscale/Activity	Walks Frequently	371 patients (14.32%)	116 patients (17.90%)
	Bed Fast	158 patients (6.10%)	41 patients (6.33%)
	Walks Occasionally	291 patients (11.24%)	83 patients (12.81%)
	Chair Fast	38 patients (1.47%)	12 patients (1.85%)
Sensory Perception	No Impairment	462 patients (17.84%)	127 patients (19.60%)
	Completely Limited	70 patients (2.70%)	16 patients (2.47%)
	Slightly Limited	284 patients (10.97%)	98 patients (15.12%)
	Very Limited	42 patients (1.62%)	11 patients (1.70%)
Mobility	No Limitations	409 patients (15.79%)	111 patients (17.13%)
	Completely Immobile	74 patients (2.86%)	15 patients (2.31%)
	Slightly Limited	137 patients (5.29%)	53 patients (8.18%)
	Very Limited	238 patients (9.19%)	73 patients (11.27%)
Nutrition Statistics	Excellent	383 patients (14.79%)	115 patients (17.75%)
	Adequate	347 patients (13.40%)	108 patients (16.67%)
	Probably Inadequate	78 patients (3.01%)	22 patients (3.40%)
	Very Poor	36 patients (1.39%)	4 patients (0.62%)
	Inadequate	14 patients (0.54%)	3 patients (0.46%)
Friction And Shear	No Potential or Apparent	686 patients (26.49%)	199 patients (30.71%)
	Friction and Shear	101 patients (3.90%)	21 patients (3.24%)
	Problem	67 patients (2.59%)	31 patients (4.78%)
	Potential Problem	2 patients (0.08%)	0 patients (0.00%)
	No Apparent Problem	2 patients (0.08%)	1 patient (0.15%)
Pressure Injury Type	No Pressure Injury	437 patients (16.88%)	118 patients (18.21%)
	Hospital-Acquired	421 patients (16.25%)	134 patients (20.68%)

4.2. Prediction Models of Pressure Injury

Model evaluation was conducted based on the different performance metrics; the following sections discuss the developed models and experiments in detail.

4.2.1. Model (A)—Potential Factors That Had a High Correlation with Pressure Injury

The potential factors that correlated with pressure injury were age, diagnosis, operation, anesthesia type, accreditation status, department category, Braden scale level,

pulse, systolic BP, length of stay, medications (Adrenaline, Norepinephrine), and lab tests (Alb, WBC, protein). The RF model had the best algorithms in this model for most of the performance metrics, followed by gradient boost and DT. Furthermore, these algorithms were compared using ROC curves, which were used to highlight the results of the models between FPR and TPR and show that the algorithms showed strong performance in comparison with the chance line (0.05), favoring RF algorithms, which had a close to perfect performance; for RF, the AUC for the ROC curve was one, as presented in Figure 7.

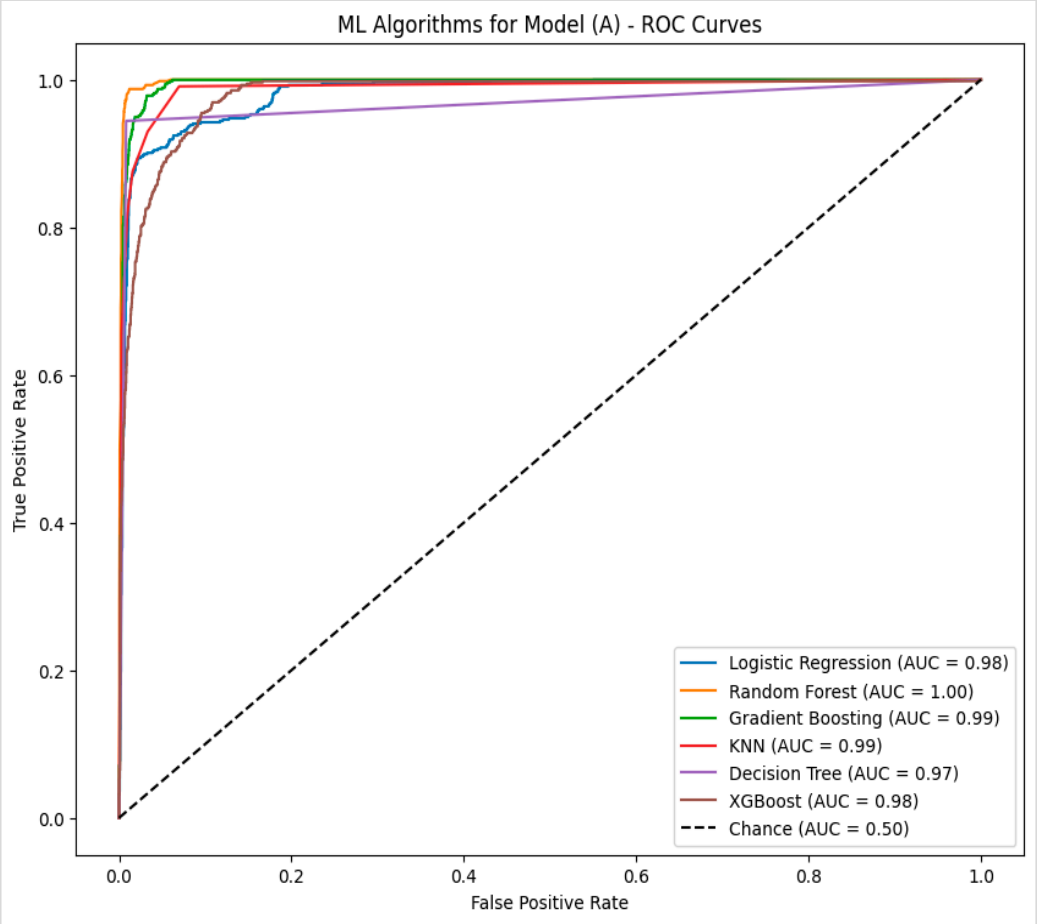

Figure 7. ML algorithms for model (A)—ROC curves.

4.2.2. Model (B)—Potential Factors with Significant Statistical Tests for Pressure Injury

The potential factors that correlated with pressure injury were gender, age, diagnosis, operation name, anesthesia type, anesthesia duration/hours, operation duration/hours, accreditation status, department category, Braden scale level, systolic BP, diastolic BP, temperature, pulse, length of stay, mechanical ventilator, sensory perception, moisture, activity, mobility, nutrition, friction and shear, lab tests (albumin, bilirubin (D), bilirubin (T), BUN, CRP, creatinine, Hb, uric acid, and WBC), and medications (Adrenalin, Nitroglycerin, and Norepinephrine). The RF model had the best algorithms in this model, along with performance metrics. Furthermore, these algorithms were compared using ROC curves, which were used to highlight the results of the model between FPR and TPR; the algorithms showed a strong performance in comparison with the chance line (0.05), favoring the RF and GB algorithms which showed close to perfect performance as their AUC for the ROC curve was 1, as presented in Figure 8.

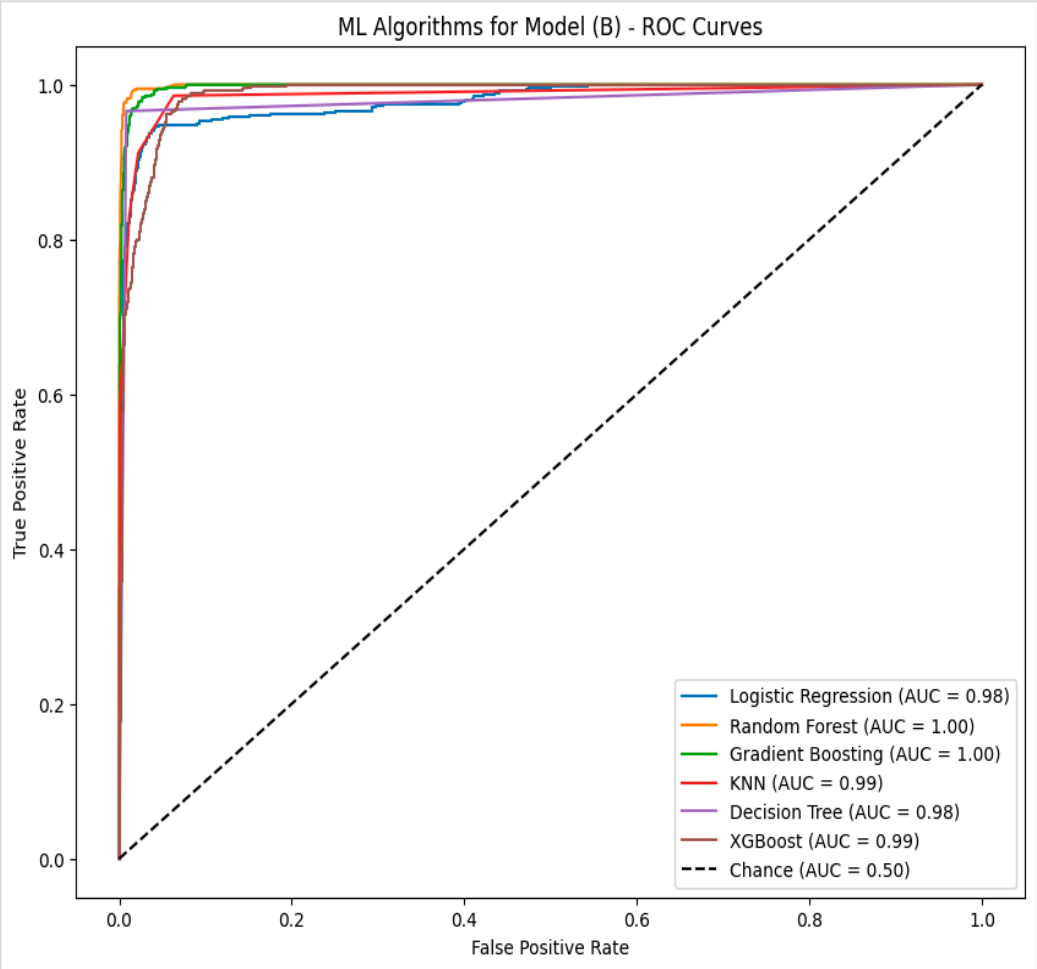

Figure 8. ML algorithms for model (B)—ROC curves.

4.2.3. Model (C)—Potential Factors with Feature Importance Related to Pressure Injury

The potential factors that had feature importance with pressure injury were gender, length of stay, hospital name, accreditation status, department category, diagnosis, operation name, sensory perception, moisture, activity, mobility, nutrition, friction and shear, laboratory test (albumin), temperature, Braden scale level, Braden score, and medications (Budicort and Vancomycin). The RF model had the best algorithms in this model, along with performance metrics. Furthermore, these algorithms were compared in using ROC curves, which were used to highlight the results of the model between FPR and TPR, and the algorithms showed a bad performance in comparison with the chance line (0.05), favoring the KNN algorithm where the AUC for the ROC curve was 1, as presented in Figure 9.

4.2.4. Model (D)—Potential Factors with a High Correlation Without Braden Scale Level

The potential factors that had a high correlation with pressure injury were age, moisture, activity, length of stay, systolic BP, and albumin. These potential factors were used to predict pressure injury by eight machine learning algorithms to find the best model and reliable model results. The RF algorithm was the best algorithm in the model, with strong performance metrics among all the algorithms. Furthermore, these algorithms were compared using ROC curves, which were used to highlight the results of the model between FPR and TPR, and the algorithms showed a strong performance in comparison with the chance line (0.05), favoring RF algorithm which showed close to perfect performance as the AUC for the ROC curve was 1, as presented in Figure 10.

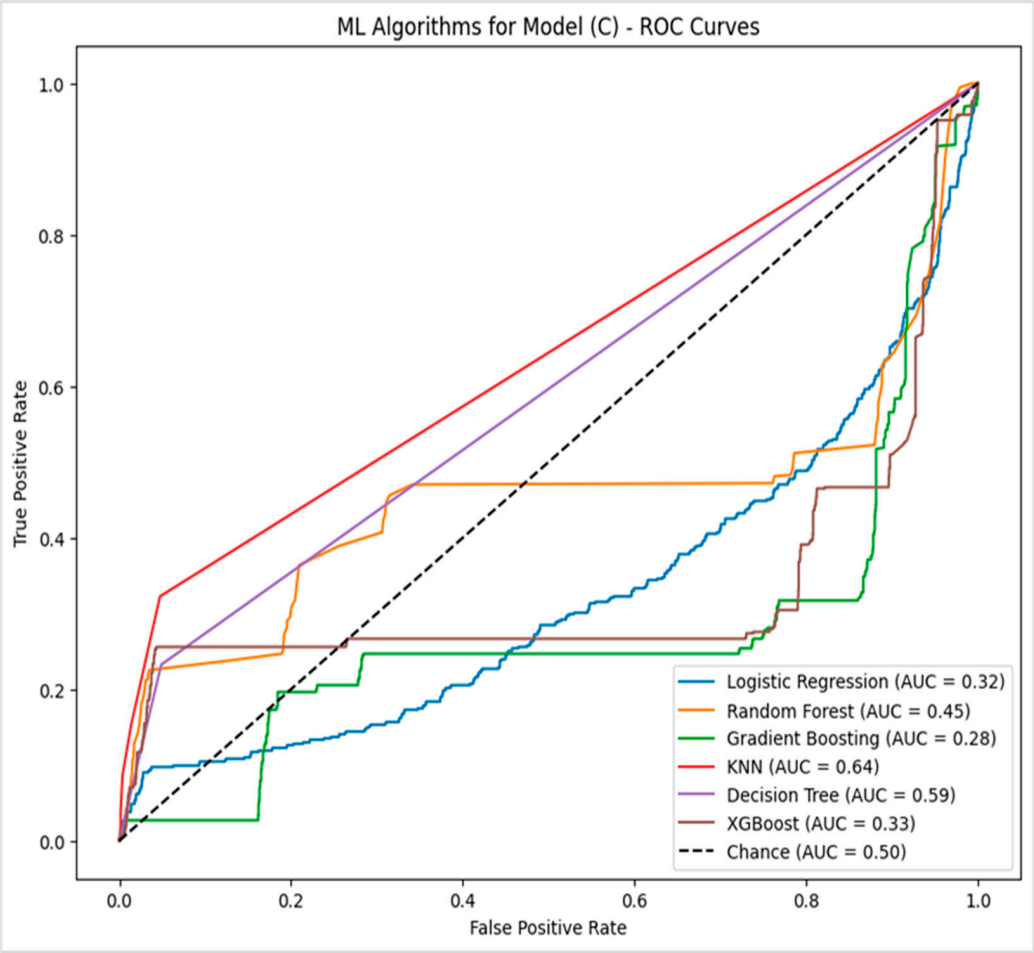

Figure 9. ML algorithms for model (C)—ROC curves.

The performance metrics among all algorithms showed excellent performance; the accuracy was (0.969–0.814), precision (0.964–0.679), recall (0.926–0.552), F1 score (0.942–0.555), AUC (0.926–0.552), FPR (0.429–0.155), and TPR was (0.807–0.361). The best model was RF, in which the accuracy was 0.962, precision was 0.942, recall was 0.922, F1 was 0.931, AUC was 0.922, FPR was 0.155, and TPR was 0.782, as presents in Table 8. Finally, the predictive variables were age, moisture, activity, LOS, systolic BP, and Alb.

Furthermore, the study findings indicate that the data from medical records can predict PI and help nurses identify patients at risk of PI earlier, which improves the quality of care and promotes patient safety. Furthermore, the study found that predictive factors in the developed model for predicting pressure injuries are not included in the traditional tools used routinely by nurses for assessing pressure injuries.

Table 8. Comparison of performance metrics of ML algorithms—all models.

		Classification							Regression	
Algorithm	**Model**	**Accuracy**	**Precision**	**Recall**	**F1**	**AUC**	**FPR**	**TPR**	**MSE**	**R2**
LR	A	0.964	0.95	0.919	0.934	0.919	0.348	0.907	NA	NA
	B	0.956	0.958	0.886	0.917	0.886	0.277	0.92	NA	NA
	C	0.828	0.649	0.514	0.486	0.514	0.58	0.4	NA	NA
	D	0.936	0.903	0.864	0.882	0.864	0.262	0.859	NA	NA
RF	A	0.988	0.98	0.978	0.979	0.978	0.028	0.88	NA	NA
	B	0.992	0.985	0.986	0.985	0.986	0.048	0.882	NA	NA
	C	0.838	0.718	0.584	0.601	0.584	0.318	0.317	NA	NA
	D	0.987	0.977	0.979	0.978	0.979	0.023	0.833	NA	NA

Table 8. *Cont.*

		Classification							Regression	
Algorithm	**Model**	**Accuracy**	**Precision**	**Recall**	**F1**	**AUC**	**FPR**	**TPR**	**MSE**	**R2**
GB	A	0.976	0.96	0.953	0.957	0.953	0.116	0.802	NA	NA
	B	0.981	0.968	0.967	0.967	0.967	0.126	0.876	NA	NA
	C	0.713	0.498	0.498	0.498	0.498	0.631	0.396	NA	NA
	D	0.967	0.939	0.946	0.942	0.946	0.048	0.742	NA	NA
KNN	A	0.966	0.947	0.93	0.938	0.93	0.162	0.753	NA	NA
	B	0.961	0.951	0.909	0.928	0.909	0.158	0.721	NA	NA
	C	0.84	0.834	0.541	0.534	0.541	0.153	0.231	NA	NA
	D	0.959	0.93	0.924	0.927	0.924	0.163	0.738	NA	NA
DT	A	0.984	0.974	0.968	0.971	0.968	0.336	0.648	NA	NA
	B	0.987	0.977	0.979	0.978	0.979	0.336	0.655	NA	NA
	C	0.828	0.677	0.592	0.609	0.592	0.35	0.411	NA	NA
	D	0.985	0.977	0.969	0.973	0.969	0.254	0.728	NA	NA
XGBoost	A	0.926	0.93	0.799	0.847	0.799	0.063	0.763	NA	NA
	B	0.939	0.946	0.833	0.877	0.833	0.044	0.787	NA	NA
	C	0.834	0.696	0.583	0.6	0.583	0.542	0.411	NA	NA
	D	0.939	0.928	0.851	0.883	0.851	0.178	0.79	NA	NA
SVR	A	NA	NA	NA	NA	NA	NA	NA	0.027	0.81
	B	NA	NA	NA	NA	NA	NA	NA	0.019	0.869
	C	NA	NA	NA	NA	NA	NA	NA	0.08	0.438
	D	NA	NA	NA	NA	NA	NA	NA	0.031	0.782
Linear	A	NA	NA	NA	NA	NA	NA	NA	0.036	0.748
	B	NA	NA	NA	NA	NA	NA	NA	0.033	0.769
	C	NA	NA	NA	NA	NA	NA	NA	0.191	−0.34
	D	NA	NA	NA	NA	NA	NA	NA	0.058	0.591

LR: logistic regression; SVR: support vector regression; RF: random forest; DT: decision tree; GB: gradient boosting; XGBoost: extreme gradient boosting; KNN: K-nearest neighbors; NA: not applicable; AUC: area under curve; TPR: true positive rate; FPR: false positive rate; F1: F1 score; R2: R squared; MSE: mean square error.

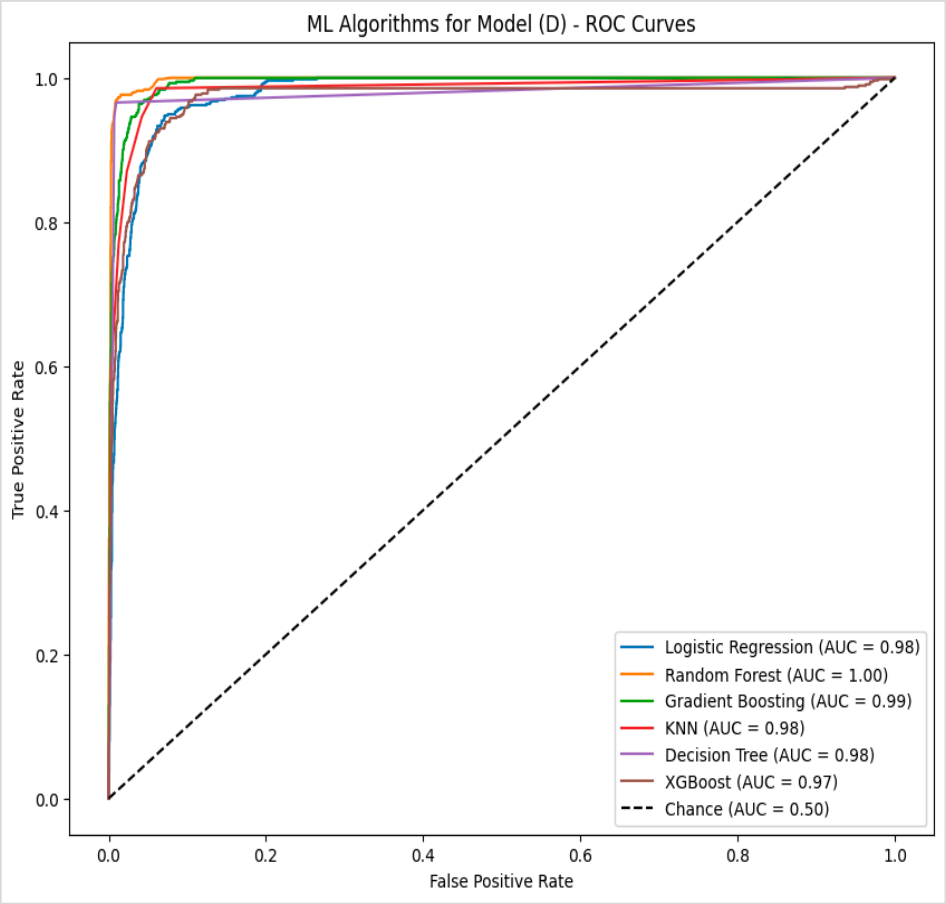

Figure 10. ML algorithms for model (D)—ROC curves.

4.2.5. Statistical Comparison of Algorithms

Accuracy—model A, model B, and model D: These models exhibited identical accuracies across all cross-validation folds, resulting in constant differences (zero standard deviation). As a result, the statistical tests comparing these models were skipped. Compared to model A, model B, and model D, model C showed no significant difference in accuracy (p-value = 0.0625 for all comparisons). However, its p-values were close to the significance threshold (0.05), suggesting a trend that may warrant further investigation with a larger dataset. For confidence intervals, the 95% confidence intervals for accuracy were as follows: model A: (0.965, 0.969); model B: (0.967, 0.971); model C: (0.812, 0.816); and model D: (0.960, 0.964).

Precision: Model A vs. model C showed a significant difference (p-value = 0.012), model B vs. model C showed s significant difference (p-value = 0.012), and model C vs. model D showed a significant difference (p-value = 0.012). For the confidence intervals, the 95% confidence intervals for precision were as follows: model A: (0.955, 0.959); model B: (0.962, 0.966); model C: (0.677, 0.681); and model D: (0.940, 0.944).

4.2.6. Results of Cross-Validation

For the confidence intervals, we calculated 95% confidence intervals for each performance metric using bootstrapping. Bootstrapping is a resampling technique that estimates the variability of a metric by repeatedly sampling the data with replacement. This provides a robust measure of uncertainty in the performance estimates. The results of the five-fold cross-validation, including the average performance metrics and their standard deviations, are presented in Table 9.

Table 9. Cross-validation results for each model and algorithm.

Model	Algorithm	Accuracy	Standard Deviation	Optimal Hyperparameters
Model A	Linear	0.744	0.021	Default
	LR	0.962	0.004	C = 1.0, solver = 'lbfgs'
	RF	0.962	0.008	n_estimators = 100, max_depth = 10
	GB	0.964	0.005	learning_rate = 0.1, n_estimators = 200
	SVR	0.769	0.021	C = 1.0, kernel = 'rbf', gamma = 0.1
	KNN	0.956	0.006	n_neighbors = 5
	DT	0.945	0.013	max_depth = 5
	XGBoost	0.964	0.009	learning_rate = 0.1, n_estimators = 200
Model B	Linear	0.759	0.009	Default
	LR	0.960	0.005	C = 1.0, solver = 'lbfgs'
	RF	0.968	0.002	n_estimators = 100, max_depth = 10
	GB	0.969	0.003	learning_rate = 0.1, n_estimators = 200
	SVR	0.757	0.026	C = 1.0, kernel = 'rbf', gamma = 0.1
	KNN	0.954	0.006	n_neighbors = 5
	DT	0.960	0.007	max_depth = 5
	XGBoost	0.968	0.007	learning_rate = 0.1, n_estimators = 200
Model C	Linear	0.766	0.008	Default
	LR	0.960	0.003	C = 1.0, solver = 'lbfgs'
	RF	0.971	0.005	n_estimators = 100, max_depth = 10
	GB	0.969	0.004	learning_rate = 0.1, n_estimators = 200
	SVR	0.778	0.027	C = 1.0, kernel = 'rbf', gamma = 0.1
	KNN	0.961	0.006	n_neighbors = 5
	DT	0.962	0.007	max_depth = 5
	XGBoost	0.968	0.003	learning_rate = 0.1, n_estimators = 200

Table 9. *Cont.*

Model	Algorithm	Accuracy	Standard Deviation	Optimal Hyperparameters
Model D	Linear	0.588	0.033	Default
	LR	0.938	0.006	C = 1.0, solver = 'lbfgs'
	RF	0.952	0.004	n_estimators = 100, max_depth = 10
	GB	0.953	0.006	learning_rate = 0.1, n_estimators = 200
	SVR	0.706	0.022	C = 1.0, kernel = 'rbf', gamma = 0.1
	KNN	0.949	0.007	n_neighbors = 5
	DT	0.943	0.006	max_depth = 5
	XGBoost	0.950	0.007	learning_rate = 0.1, n_estimators = 200

LR: logistic regression; SVR: support vector regression; RF: random forest; DT: decision tree; GB: gradient boosting; XGBoost: extreme gradient boosting; KNN: K-nearest neighbors; max: maximum; C: regularization parameter; n: number; lbfgs: limited-memory Broyden–Fletcher–Goldfarb–Shanno; rbf: radial basis function.

5. Discussion

This section presents a discussion of the findings with related studies conducted previously, with an explanation of the findings by the researchers from a Palestinian point of view. The discussion presents the interpretation of the results and the model comparison.

The proposed models had different factors (features) that were used in each model, and the developed models were measured and evaluated by standard performance metrics for both types of algorithms (classifications and regression tasks). The results of model (A), model (B), and model (D) are considered good, and there was a strong performance by the three models based on their performance metrics.

The averages of each performance metric for model (A) were as follows: accuracy was 0.967, precision was 0.957, recall was 0.924, F1 was 0.938, AUC was 0.924, FPR was 0.176, and TPR was 0.792. For model (B), they were as follows: accuracy was 0.969, precision was 0.964, recall was 0.926, F1 score was 0.942, AUC was 0.926, FPR was 0.165, and TPR was 0.807. For model (C), they were as follows: accuracy was 0.814, precision was 0.679, recall was 0.552, F1 score was 0.555, AUC was 0.552, FPR was 0.429, and TPR was 0.361. For model (D), they were as follows: accuracy was 0.962, precision was 0.942, recall was 0.922, F1 score was 0.931, AUC was 0.922, FPR was 0.155, and TPR was 0.782, as is presented in Table 10.

Table 10. Performance metrics for developed models.

Model	Accuracy	Precision	Recall	F1	AUC	FPR	TPR
Model A	0.967	0.957	0.924	0.938	0.924	0.176	0.792
Model B	0.969	0.964	0.926	0.942	0.926	0.165	0.807
Model C	0.814	0.679	0.552	0.555	0.552	0.429	0.361
Model D	0.962	0.942	0.922	0.931	0.922	0.155	0.782

Model (A) predicts PI with 12 predictive risk factors and 3 biomarkers, as follows: gender, age, diagnosis, operation name, anesthesia type, anesthesia duration/hours, operation duration/hours, accreditation status, department category, Braden scale, systolic BP, diastolic BP, temperature, pulse, LOS, mechanical ventilator, sensory perception, moisture, activity, mobility, nutrition, friction and shear, Alb, bilirubin (D), bilirubin (T), (BUN), CRP, creatinine, Hb, uric acid, WBC, Adrenalin, Nitroglycerin, and Norepinephrine. Model (B) predicts PI with 24 predictive risk factors and 9 biomarkers, as follows: age, diagnosis, operation, anesthesia type, accreditation status, department category, Braden scale, pulse, systolic BP, LOS, Adrenaline, Norepinephrine, Alb, WBC, and protein. Model (D) predicts PI with five predictive risk factors, age, moisture, activity, LOS, and systolic (BP), and one biomarker, Alb.

Model (D)'s performance is high, and its performance metrics are as follows: accuracy: 0.962; precision: 0.942; recall: 0.922; F1 score: 0.931; AUC: 0.922; FPR: 0.155; and TPR: 0.782. The slight differences between the three models in the performance metrics are as follows: accuracy: (model A: 0.967; model B: 0.969; model D: 0.962); precision: (model A: 0.957; model B: 0.964; model D: 0.942); recall: (model A: 0.924; model B: 0.926; model D: 0.922); F1: (model A: 0.938; model B: 0.942; model D: 0.931); AUC: (model A: 0.924; model B: 0.926; model D: 0.922); FPR: (model A: 0.176; model B: 0.165; model D: 0.155); and TPR: (model A: 0.792; model B: 0.807; model D: 0.782); as presented in Table 7.

Based on the comparison between performance metrics among all the models, the data show that model (B) has the best performance metrics, followed by model (A) and model (D), and that the RF algorithm was the best in the three models.

The major issue in the comparison is that model (B) utilized double the features of model (A) to predict pressure injury with an advanced setup, considering factors such as a mechanical ventilator that may not be used in many patients' conditions, especially for patients treated in open units. In addition, there were nine biomarkers utilized in model (B), triple the biomarkers utilized in model (A), which means that they were not captured by some of the patients. This is relevant due to the models' efficiency, that has become a major consideration in the healthcare industry.

Model (D), in comparison with the other two models (A) and (B), has a reasonable number of features, with only six predictive risk factors, and does not use the medications used in the two previous models, which overlook the patients who were not in intensive units and did not need any vasopressor medications. Also, this model did not rely on the department category (open or intensive units) or the accreditation status of the hospital, which makes it more fit for all types of hospitals.

In addition, this model did not require many biomarkers to predict pressure injury and only utilized the Alb level, which made this model efficient and more practical. Finally, model (D) did not rely on the screening results of the traditional screening tool (Braden scale) as (A and B) did, which makes this model more flexible with hospitals that use other tools for assessing the patients, or do not use structured screening tools.

Having taken all these considerations into account, and given the excellent performance metrics in all models (A, B, and D), with slight differences, which were not significant, we recommend model (D), with the following performance metrics: accuracy: 0.962; precision: 0.942; recall: 0.922; F1: 0.931; AUC: 0.922; FPR: 0.155; and TPR: 0.782. It will be more effective and practical in the real world and can be utilized by in all hospitals' adult settings.

The identical performance of models A, B, and D across all folds suggests that these models are highly similar in terms of predictive performance. This could be due to the use of similar algorithms, hyperparameters, or the limited variability in the dataset. Future work could explore larger or more diverse datasets to further differentiate these models. In contrast, model C showed significantly lower precision compared to the other models, indicating that it may produce more false positives. However, there was no significant difference in accuracy, suggesting that model C compensated for its lower precision with higher recall or other performance aspects. Although the differences in accuracy were not statistically significant, its p-values were close to the significance threshold. This trend suggests that with a larger dataset or more cross-validation folds, significant differences might emerge.

The rigorous hyperparameter tuning process ensured that each algorithm was optimized for the given dataset. This step was critical to achieving competitive performance and ensuring fair comparisons between the algorithms. The use of five-fold cross-validation provided a robust estimate of model performance and minimized the risk of overfitting.

The small standard deviations observed in the cross-validation results (e.g., ±0.002 for accuracy) indicate that the models are stable and generalize well to unseen data.

Model (D) shows excellent performance metrics among all eight algorithms; for the classification algorithms, all performance metrics were high, such as accuracy, precision, recall, F1 score, and AUC. For regression algorithms, the model had a good fit, and the average difference of the squares between the predicted and actual values was low, with an MSE of 0.031. The R2 was about 78% of the variations in the targeted variable (pressure injury) detected by the potential factors in the developed model (features). In this model, the RF algorithms had the best overall performance metrics in comparison with the other classification algorithms, and SVR was the best of the regression algorithms.

Finally, the results of RF as the best algorithm are compatible with the findings of [69], a meta-analysis study which found that RF was the best algorithm to predict pressure injury, with high performance metrics; with [39], which found that RF was the best algorithm, with a high accuracy; with [50], which found that RF was the best algorithm among all algorithms to predict pressure injury; and with [70], a systematic review study which found that LR and RF were the best algorithms to predict pressure injury. Moreover, [55], a systematic review study, also found that RF was the best out of the 16 reviewed algorithms to predict pressure injury, and study [46] found that RF was the best algorithm, with excellent performance metrics.

This study utilized a novel fused multi-channel prediction model and utilized eight machine learning algorithms, which makes these models unique and more comprehensive. The number of algorithms and prediction models discussed in some previous studies was four algorithms, such as in [39] which utilized LR, RF, SVR, and NN. Other studies utilized 6 algorithms, such as [69], a meta-analysis study which reviewed 25 studies, and the maximum number was 6 algorithms (DT, diagnostic odds ratio, LR, NN, RF, and SVR). Other studies ranged from one to six algorithms, such as [55], a systematic reviewed study, and those algorithms were LR, DT, SVR, KNN, MLP, and XGBoost. Another study used only two algorithms, [46], which utilized (RF and LR).

This study also developed model (D), which can predict pressure injury among different departments or different specialties in adult hospital settings, which is considered an added value to the knowledge. Previous prediction models developed in the previous literature were designated to certain departments such as the ICU or CCU [20,22,41–43,45,48,49,51,53,71]; or to certain diseases, such as [47], which developed a model for oncology, and [52], which developed a model for cardiac surgery; or for certain patient groups, such as [10,46] which developed models for surgical patients.

While the study provides a brief overview of previous research, a more detailed comparison of the "EADB" model with state-of-the-art models in similar contexts is essential to highlight its competitive edge. Existing models for pressure injury prediction often rely on traditional risk assessment tools or focus narrowly on a limited set of features, which can limit their accuracy and adaptability. In contrast, the "EADB" model integrates a comprehensive set of predictors, including risk factors, biomarkers, and incident reports, leveraging the strengths of eight machine learning algorithms to achieve high predictive performance. Compared to models reported in prior studies, the "EADB" model benefits from a balanced dataset and incorporates advanced techniques for mitigating biases and optimizing accuracy. Future work will include benchmarking the model against leading approaches in the literature, emphasizing its potential to outperform conventional methods in terms of predictive accuracy, generalizability, and clinical utility.

6. Conclusions

This research provides evidence of the feasibility of developing multi-fused prediction models to predict pressure injury for hospitalized patients by utilizing the potential risk factors and biomarkers that are routinely available in electronic patient medical records. The developed prediction models had strong performance metrics, which means that the final model is reliable and valid with different approaches to validation. These models recruit multiple potential factors (features) that can detect pressure injury in different levels of care and at different rates of severity or acuity of patient conditions. The approach used in developing a prediction model of pressure injury provides evidence that for the prediction of pressure injury utilizing different potential factors it is hard for healthcare providers and nurses to follow the predictive risk factors daily. This provides valuable assistance to nurses, which will be reflected in the quality of nursing care provided to the patients and maintain patient safety through preventing or reducing the risk of pressure injury for patients. Finally, the predictive model of pressure injury, based on the novelty of this new approach and on its strong performance metrics in predicting pressure injury, is considered a promising tool for the future.

The prediction model of pressure injury will assist nurses and healthcare providers in enhancing the quality of care and improving patient experience and satisfaction through minimizing harm that may affect patients' quality of life and the care process. The rapid progression in utilizing electronic medical records in the healthcare industry is leading healthcare facilities to gain the technological benefits of using electronic medical records and look for additional features that can be generated from these technologies. These issues need to be taken into consideration as an area for improvement to enhance the quality of data in electronic patient medical records, which would be reflected in the quality of care, improve the continuity of care, and ensure that patient medical records and HIS will help hospitals in their mission and goals.

Moreover, based on the results obtained from this research, it is recommended that nursing scientists and nursing practitioners need to upgrade their methods of assessing pressure injuries. This upgrade should include the factors that were not assessed in traditional tools, such as (age, length of stay, systolic blood pressure, and albumin levels), and consider the findings of the different prediction models of pressure injury.

Using a prediction model which utilizes machine learning approaches for clinical services addresses several challenges that relate to usability and reliability in real practice; in addition to this is the question of how to integrate with electronic health record systems to support real-time clinical decision making without disrupting established workflows. Moreover, the model's interpretability and transparency are crucial to fostering trust and acceptance among healthcare providers, who may be unfamiliar with machine learning. Furthermore, the ethical issues including data confidentiality and compliance with local regulations must be addressed to maintain patient information. Finally, implementing such models requires full awareness for users to maximize their potential impact and the benefits from using such models. These considerations highlight the importance of aligning technological advancements with practical clinical concerns to improve patient care outcomes effectively.

7. Limitations of the Study

No study is without limitations; the first one for this study is the quality of data documented by the healthcare providers in the medical records. This challenge was overcome through data cleaning and data preparation before building the model to achieve the best accuracy and make sure that the data are valid and reliable. The second one is related to the fact that the findings of the study are based on three hospital records in Palestine; the

developed prediction model (EADB) utilized data from three hospitals is Palestine, which provides an added value to the existing practices and a valuable contribution to knowledge and to the local Palestinian healthcare system. However, using this model in the other populations or different demographics requires careful considerations, such as different electronic health record systems, demographics, and the fact that other risk factors may affect the performance of the developed model when applied in another context. Further studies are needed to validate the models in different health systems, different electronic health record systems, and diverse populations to ensure the applicability and reliability of the developed model in various contexts.

Author Contributions: Conceptualization, E.D.B. and A.Y.O.; methodology, E.D.B., A.Y.O., M.A. and M.O.; formal analysis, E.D.B., A.Y.O. and M.O.; investigation, E.D.B. and A.Y.O.; resources, E.D.B.; data curation, E.D.B.; data visualization, E.D.B. and A.Y.O.; writing—original draft preparation, E.D.B.; writing—review and editing, E.D.B., A.Y.O., M.A. and M.O.; supervision, A.Y.O., M.A. and M.O.; project administration, A.Y.O., M.A. and M.O. All authors have read and agreed to the published version of the manuscript.

Funding: The author declares that there is no external funding.

Institutional Review Board Statement: Ethical approval was obtained from the Arab American University's (AAUP) IRB committee under number 2023/A/92/N.

Informed Consent Statement: A consent form was obtained from the hospitals to receive the data from the hospital database.

Data Availability Statement: The data will be available from the corresponding author upon reasonable request.

Acknowledgments: The authors acknowledge the hospitals that gave their permission to conduct the study.

Conflicts of Interest: The authors declare no conflicts of interest.

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