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Research article

Predicting factors for extremity fracture among border-fall patients using machine learning computing

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ABSTRACT

Background: The factors causing the injuries sustained from falls at US-Mexican border include falls from border wall or fence, fleeing from border patrols, ejecting from vehicle, and others. This study aimed to determine the factors leading to anatomical injuries and to identify the importance of factors leading to limb fracture and internal organ injuries.

Methods: A total of 178 patients who sustained musculoskeletal injuries or internal organ injuries and were admitted to our hospital were included in this retrospective study. Factors indexed for analysis included demographics, comorbidities, and falling mechanic factors. Correlations between anatomical injuries and mechanical injuries were analyzed. Multilayer perceptron neural network (MPNN) was used to identify predictive factors and to stratify the importance of these factors leading to injuries. The SPSS software was used for statistical analysis and predictive factor analysis.

Results: The extremity fracture was associated with border wall/fence fall ($p = 0.001$) and fleeing ($p = 0.002$). The spine fracture was correlated with bridge jump/fall ($p = 0.007$), fence jump/fall ($p = 0.026$). The vehicle ejecting/MVA was correlated with head injury ($P < 0.001$), chest injury ($P < 0.001$), and abdominal injury $p < 0.001$). MNPP stratify the importance of factor causing injury with multiple factor considered.

Conclusion: The various injury factors caused different anatomical injuries. Multifactorial assessment associated with these injuries can improve the accuracy of diagnosis and develop a predictive model for clinical applications.

1. Introduction

Injuries from the falls are very common injuries among undocumented immigrants at the United States-Mexico border - a special cohort of injury patients [1–4]. The number of border fall injury patients has increased with more injury severity since 2019 [5,6], which accounts for a significant proportion of patients treated annually at trauma centers [7]. Significant medical treatment costs are required to treat these injuries leading to a substantial loss of productivity which affects the community both directly and indirectly [7].

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Among this cohort of patients, musculoskeletal injuries from border wall/fence are the primary reason for seeking medical treatments [8–11]. The height of border fence wall has increased, subsequently leading to the increased the rate of multiple organ injuries and injury severity that required multiple surgical interventions and a longer length of stay (LOS) [1,5]. The border falls has now accounted for a significant percentage of morbidity and mortality sustained among the undocumented immigrants [12].

The trauma causes in this study included falling from a border fence, fall on the rough terrain, fleeing away from border patrol, motor vehicle accidents (MVA) or ejecting from a vehicle, and a water crossing or bridge [6,7]. The most common injury is extremity fracture (EF), but there are other injuries including injuries of head, chest, and abdomen, which are more fatal. The internal organ injuries can be overlapped by limb fracture leading to ignorance of examination of internal organ injury, potentially increasing the risk of misdiagnosis or delaying the early treatment of lethal injury [13,14].

We hypothesized that injury hazards such as mechanical factors among the cohort of patients in our study are important in accurate diagnosis which can be influenced by demographics and comorbidities. Traditional statistical bivariate analysis only determines the correlation between two variables. The emerging machine learning algorithms such as multilayer perceptron neural network (MPNN) has been used to analyze cause and effect with multiple factors considered to identify the predictive factors and the importance of factors in diagnosis [15]. Our research goal was to determine the factors leading to anatomical injuries and to identify the importance of factors leading to limb fracture and internal organ injuries.

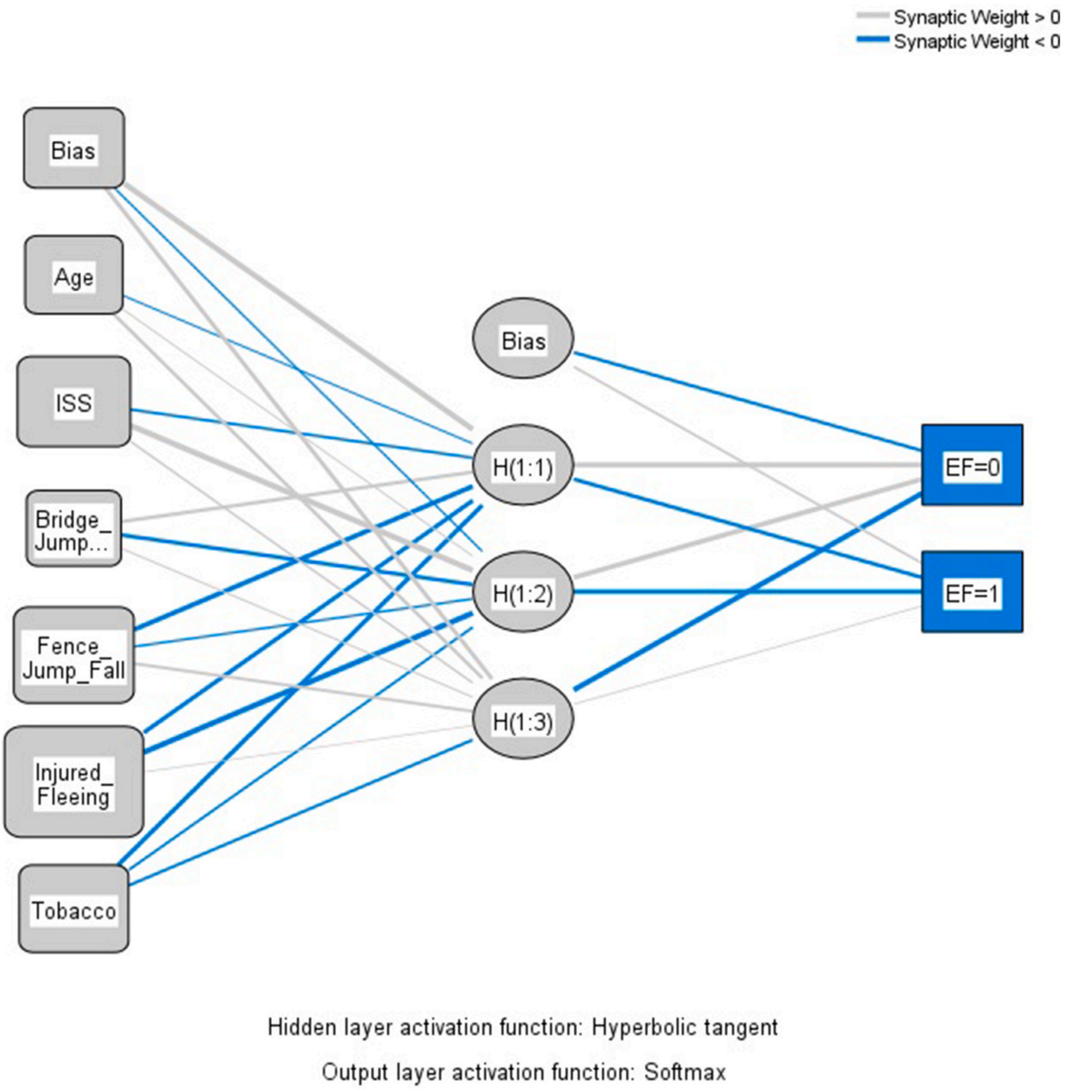

Fig. 1. The MPNN ML structure for prediction of factors contributing to extremity fracture. The dependent variable is “extremity fracture” (EF) and the covariables include demographics and mechanical factors.

2. Materials and methods

2.1. Patients

The patients who sustained musculoskeletal injuries or internal organ injuries from falls and admitted to our hospital were included in this retrospective study. The trauma registry queried for patients who were admitted to our hospital brought by U.S. Customs and Border Protection (CBP) agents. An ethics committee approval was obtained to conduct this retrospective study from the Western Institutional Review Board (South Texas Health System, 20216226).

2.2. Data collection

The variables selected for this retrospective study included demographics (age, sex, race, and others), comorbidities, self-reported social risk factors (alcohol, tobacco, pregnancy, intravenous drug abuse), country of origin, Glasgow Coma Scale (GCS), injury severity score (ISS), intense cure unit (ICU) stay, and length of stay (LOS) in the hospital, mechanism of injury (mechanical factors), and anatomical locations of injuries such as head/brain, chest, abdomen, spine, pelvis, and extremities.

2.3. Statistical analysis

Descriptive statistical analysis was performed for demographics, country of origin, comorbidities, self-reported social risk factors (alcohol, tobacco, pregnancy, intravenous drug abuse), location of the fracture, and the mechanical factor leading to fracture. SPSS software (Version 28, IBM, Armonk, NY) was used to perform the *t*-test, Chi-Square test, and bivariate correlation analyses. A p-value <0.05 was considered significant.

2.4. Machine learning predictive modeling

The multilayer perceptron neural network (MPNN) methods were used to build a predictive model to identify the factors contributing to injury and to stratify importance of factors (Fig. 1). The cause-and-effect relationships were considered in selecting predictors. The dependent variable was an individual anatomical injury. Predicting factors included ISS, GCS on admission, age, fence-jump/fall, injured fleeing, comorbidity, bridge-jump/fall, and other variables that had significant correlation with injury based on bivariate correlation analysis.

A 70:30 training-testing split was used for dataset partition. The MPNN architecture included one hidden layer and 50 units at maximum in the hidden layer using an automatic architecture selection function. Each hidden unit is a function of the weighted sum of the inputs. A batch with the automatic method was selected for the training type. The scaled conjugate gradient was used for the optimization algorithm. The initial learning rate was 0.4. Hyperbolic tangent was applied for the activation function in the hidden layer and Softmax was used for the activation function in the output layer. The loss function was cross-entropy. The Bayesian method

Table 1
Demographic data of extremity fracture.

	Extremity Fracture			
	No	**Yes**	p-value	95 % CI
	n = 71	n = 107		
Age	Mean ± SD 28.1 ± 11.3	Mean ± SD 33.2 ± 10.4	0.003[a]	29.7–32.9
Gender				
Female	26(36.6 %)	36(33.6 %)	0.683[b]	0.577–0.721
Male	45(63.4 %)	71(66.4 %)		
Ethnicity				
African	1(1.4 %)	0(0.0 %)	0.160[b]	0.936–0.991
Hispanic or Latino	67(94.4 %)	106(99.1 %)		
Not Hispanic or Latino	3(4.2 %)	1(0.9 %)		
Country				
Mexica	19(26.8 %)	44(41.1 %)	0.016[b]	0.284–0.429
El Salvador	7(9.9 %)	20(18.7 %)		
Honduras	16(22.5 %)	18(16.8 %)		
Guatemala	22(31.0 %)	14(13.1 %)		
Others[c]	7(9.9 %)	11(10.3 %)		
Yes	1(1.4 %)	5(4.7 %)		

c- Chi Square Fisher Exact test.
[a] *t*-test.
[b] Chi Square Pearson test.
[c] Others include Belize (n = 2), Brazil (1), China (2), Colombia (1), Cuba (3), Ecuador (1), Romanian (1), Venezuela (1), and an Unknown country (6).

was applied for regularization. Predicting outcome was summarized as EF (Yes vs. No). The importance of predictive variables was calculated based on a sensitivity analysis, which computed the importance of each predictor in the neural network [16].

3. Results

3.1. Clinical profiles

The patient's age ranged from 4 to 67 years (31.3 ± 10.8) (Mean ± SD). The EF patients had an elder age (33.2 ± 10.4) than non-extremity patients (28.1 ± 11.3) ($p = 0.003$). The rate of EF in males (61.2 %) was not significantly higher than in females (58.1 %) ($p = 0.683$) (Table 1). In this study, 97.2 % were of Hispanic or Latino ethnicity, there was not a statistically significant difference in extremity fracture among ethnicities ($p = 0.160$). The country of origin was mostly Mexico (35.4 %), followed by Guatemala (20.2 %), Honduras (19.1 %), or El Salvador (15.5 %), the patients from Mexico had a higher rate of EF (41.1 %) compared with another origin of countries (Table 1).

Approximate 10 % of patients had comorbidities, there was not a statistical difference between the patients of extremity fracture and non-fracture regarding comorbidity including hypertension, diabetes mellitus, hyperlipidemia, cerebrovascular accident, gastroesophageal reflux disease, and tuberculosis ($p > 0.1$) (Table 2).

Among self-reported social risk factors, smokers had a higher EF rate ($p = 0.009$). No statistically significant correlation was found between EF and other factors including alcohol, pregnancy, and IVDA ($p > 0.4$) (Table 3).

3.2. Profile of anatomical injuries

One hundred and seven patients sustained extremity fractures (60.1 %, 107/178). Forty-one patients sustained spine fracture (23.0 %, 41/178). Most of these EF were closed fractures (n = 86, 48.3 %, 86/178). Twelve patients sustained pelvic fracture (6.7 %, 12/178). Seventeen patients sustained head injury (9.6 %, 17/165). Seventeen patients sustained chest injury (11.2 %, 20/165). Three patients sustained abdominal injury (1,7 %, 3/178). EF had the highest injury rate (Chi-Square Bonferroni correction test, $p < 0.001$).

3.3. Correlations between injuries and mechanic variables

EF was positively correlated with fence jump/fall ($p = 0.001$), injured fleeing ($p = 0.002$) suggestive of these two mechanic factors be the major reason for extremity fracture. EF was negatively correlated with assault ($p < 0.001$) and MVA ($p < 0.001$) suggestive of assault or MVA was the least mechanic factor leading to EF, but higher chance for head, chest or abdominal injuries (Table 4).

Table 2
Comorbidities of extremity fracture.

	Extremity Fracture			
	No	**Yes**	p-value	95 % CI
	n = 71	n = 107		
Comorbidity Yes or No				
No	65(91.5 %)	92(86.0 %)	0.379[b]	0.075–0.175
Yes	6(8.5 %)	15(14.0 %)		
Hypertension (HTN)				
No	69(97.2 %)	101(94.4 %)	0.480[c]	0.020–0.087
Yes	2(2.8 %)	6(5.6 %)		
Diabetes Mellitus (DM)				
No	69(97.2 %)	104(97.2 %)	1.000[c]	0.009–0.064
Yes	2(2.8 %)	3(2.8 %)		
Hyperlipidemia (HLD)				
No	71(100.0 %)	105(98.1 %)	0.518[c]	0.001–0.040
Yes	0(0.0 %)	2(1.9 %)		
Asthma				
No	71(100.0 %)	106(99.1 %)	1.000[c]	0.000–0.031
Yes	0(0.0 %)	1(0.9 %)		
Cerebrovascular Accident (CVA)				
No	71(100.0 %)	106(99.1 %)	1.000[c]	0.006–0.057
Yes	0(0.0 %)	1(0.9 %)		
Gastroesophageal Reflux Disease (GERD)				
No	70(98.6 %)	104(97.2 %)	1.000[c]	0.009–0.064
Yes	1(1.4 %)	3(2.8 %)		
Tuberculosis				
No	65(98.5 %)	101(98.1 %)	1.000[c]	0.001–0.040
Yes	1(1.5 %)	2(1.9 %)		

[b] Chi Square Pearson test.
[c] Chi Square Fisher Exact test.

Table 3
Self-reported social risk factors.

	Extremity Fracture			
	No	**Yes**	p-value	95 % CI
	n = 71	n = 107		
Tobacco				
No	68(95.8 %)	88(82.2 %)	0.009[c]	0.079–0.181
Yes	3(4.2 %)	19(17.8 %)		
Alcohol				
No	70(98.6 %)	102(95.3 %)	0.404[c]	0.012–0.072
Yes	1(1.4 %)	5(4.7 %)		
Pregnancy				
No	10(37.0 %)	0(0.0 %)	1.000[c]	0.000–0.038
Yes	17(63.0 %)	1(100.0 %)		
Intravenous Drug Abuse (IVDA)				
No	71(100.0 %)	105(98.1 %)	0.518[c]	0.001–0.040
Yes	0(0.0 %)	2(1.9 %)		

b – Chi Square Pearson test.
[c] Chi Square Fisher Exact test.

Table 4
Correlations between injury and mechanical factors.

		Extremity Fracture	Spine Fracture	Pelvis Fracture	Head Injury	Chest Injury	Abdomen injury
Assault	Correlation Coefficient	−0.260	−0.095	−0.016	0.213	0.117	−0.044
	P Value	0.000	0.104	0.417	0.003	0.060	0.280
Bridge Jump/Fall	Correlation Coefficient	0.030	0.185	0.065	0.016	0.005	−0.043
	P Value	0.343	0.007	0.194	0.418	0.471	0.286
Fence Jump/Fall	Correlation Coefficient	0.241	0.146	0.045	−0.211	−0.216	−0.093
	P Value	0.001	0.026	0.274	0.003	0.002	0.108
Injured fleeing	Correlation Coefficient	0.219	−0.199	−0.037	−0.091	−0.149	−0.070
	P Value	0.002	0.004	0.310	0.123	0.024	0.175
MVA	Correlation Coefficient	−0.308	0.074	−0.001	0.256	0.363	0.174
	P Value	0.000	0.162	0.493	0.000	0.000	0.010
Other Injury Cause	Correlation Coefficient	−0.103	−0.160	−0.079	−0.011	0.028	0.124
	P Value	0.086	0.017	0.149	0.446	0.354	0.050

The spine fracture was positively correlated with bridge jump/fall ($p = 0.007$), fence jump/fall ($p = 0.026$), indicating that the falling from fence or bridge is an important mechanic leading to spine fracture. The spine fracture was negatively associated with injured fleeing suggestive of injure fleeing had a less chance for spine fracture (Table 4).

Head injury was positively correlated with assault ($p < 0.000$) or MVA ($P < 0.001$), suggesting that assault or MVA can be the major mechanical for head injury. Head injury was negatively associated with fence jump/fall, suggesting that fence jump/fall was not a common mechanical factor for head injury (Table 4).

Chest injury was positively correlated with MVA ($P < 0.001$), indicating that MVA had a higher chance leading to chest injury than other anatomical injuries. Chest injury was negatively associated with fence jump/fall or injured fleeing suggesting that fence jump/fall or fleeing had a less chance leading to chest injury (Table 4).

Abdominal injury was positively correlated with MVA ($P < 0.001$), suggestive of higher abdominal injury rate in MVA (Table 4).

In terms of mechanical factors for injuries, assault caused head injury and chest injury, falling from bridge caused spine fracture, falling from fence caused EF and spine fracture, injured fleeing caused EF, MVA mainly caused head, chest, or abdominal injuries.

Table 5
Accuracy of MPNN model training and testing.

Sample		Predicted		
		No	Yes	Percent Correct
Training	No	36	18	66.7 %
	Yes	9	68	88.3 %
	Overall Percent	34.4 %	65.6 %	79.4 %
Testing	No	12	8	60.0 %
	Yes	3	34	91.9 %
	Overall Percent	26.3 %	73.7 %	80.7 %

Dependent Variable: EF.

3.4. Machine learning model in predicting the injury cause for extremity fracture

The accuracy of MPNN model training for extremity fracture predictive model was 88.3 % and non-fracture was 66.7 % with an overall accuracy of 79.4 %. The accuracy of MPNN model performance was validated to be 60.0 % for non-fracture and 91.9 % for extremity fracture with an overall accuracy of 80.7 % (Table 5).

The AUC value of ROC was 0.851 for EF classification (Fig. 2). MPNN predictive model ranked the most important predictor for EF to be ISS followed by fence-jump/fall, tobacco use, age, GCS at admission, injured fleeing, and bridge-jump/fall (Fig. 3).

4. Discussion

4.1. Justification of this study

Severe trauma is the leading reason causing death among middle-aged people. The earlier accurate diagnosis and treatment of injuries and hidden complications are of great significance to reduce trauma deaths. Our research goal is to build AI predictive models to assist clinical diagnosis of fall injuries aiming at quality improvement (QI) of clinical practice using the clinical data of our trauma patients. This study focused on extremity fracture (EF) of border-falls from various fall mechanisms including fence fall, bridge fall, vehicle ejection, fleeing, assault and others. With all these variable input into a predictive model, the computer can assist in clinical diagnosis aiming at multiple factors considered (including mechanic factors) to detect hidden complications and other potential anatomical injuries on the admission in emergence department.

4.2. Summary of findings

Identifying injury patterns in complex feature sets has the potential to produce more accurate diagnosis and avoid misdiagnosis. This study demonstrated that an MPNN-based AI model can be built for a predictive model of EF diagnosis among the patient specific to border falls. The MPNN predictive model showed that the GCS and fence jump/fall were key factors associated with EF among this cohort of patients. The accuracy of the performance was excellent with an AUC of ROC curve to be 0.851 demonstrating its excellent efficiency in EF prediction [16,17].

MPNN ranked the strongest predictors for EF to be GCS on admission, followed by fence-jump-fall, injured fleeing, age, and other factors (Fig. 3). MPNN was selected in this study because it is one of the most used neural network architectures. MPNN makes good classifier algorithms and has been used in medical research [18–20].

4.3. Bivariate correlation analysis

The strength of the correlation between EF and other factors can be determined by correlation coefficients, in which ± 1 indicates the strongest association and 0 indicates no relationship [21]. In this study, the factors positively correlated with EF were age, use of tobacco, ISS, GCS on admission, fence-related jumping or fall, and injured fleeing. MVA or assault had a negative correlation with EF suggesting MVA, or assault led to a higher rate of other anatomical injuries such the head or abdominal injuries (Table 4).

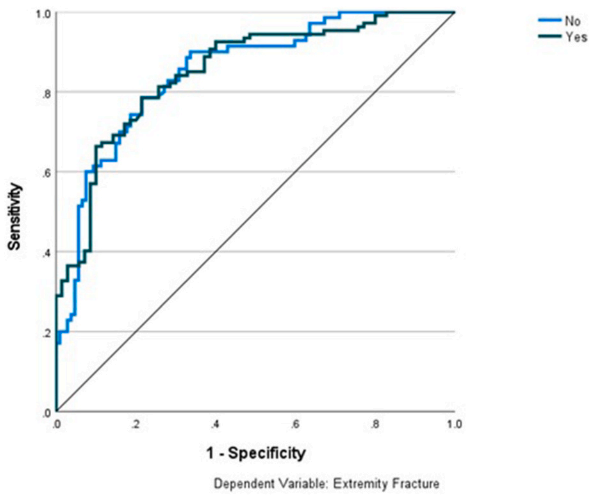

Fig. 2. Sensitivity and specificity of MPNN in predicting extremity fracture. The area under the curve (AUC is 0.851).

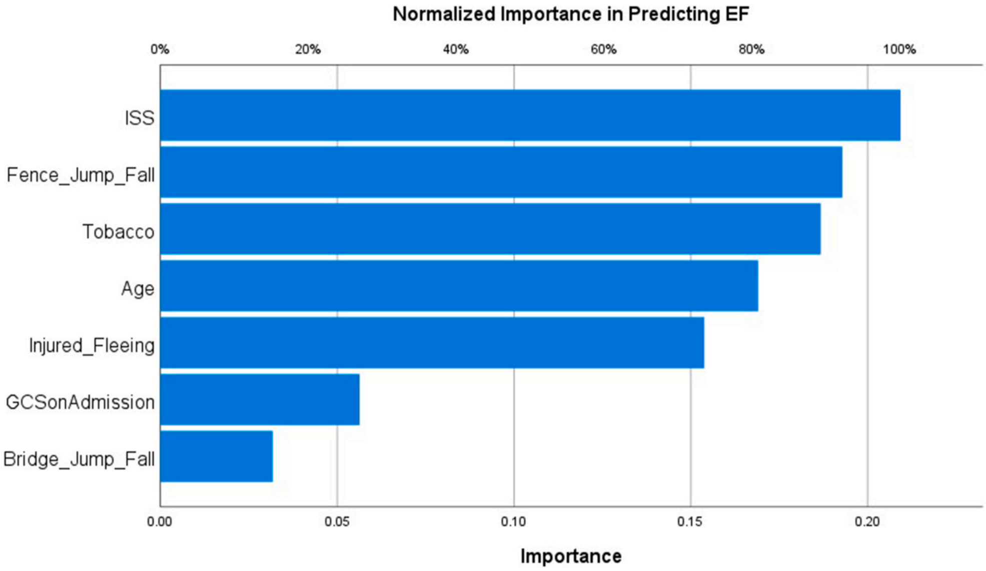

Fig. 3. Normalized importance of individual factors contributing to EF predicted by MPNN.

4.4. *Selection for ML predictive model*

MPNN, a forward artificial neural network, has stacked multiple layers of perceptron, including an input layer, one or more hidden layers, and an output layer. The model is trained via backpropagation using stochastic gradient descent. It is one of the most commonly used neural network architectures. MPNN has been used in medical and orthopaedic research [18–20]. It allows for approximate solutions for complex problems to better understand the correlation strength between multiple variables [22,23].

4.5. *Clinical relevance*

The AI methods have the potential to capture underlying trends and patterns, otherwise impossible with previous conventional statistics capabilities [24], thus to assist in clinical diagnosis [25]. The MPNN predictive model has been utilized in clinical quality improvement practices and emergency care to reduce complications and costs [23,24]. In this study, we used MPNN to understand the critical mechanic factors leading to EF as well as underlying potential injuries in other anatomic locations. When the predictive model does not suggest an EF, other anatomical injuries should be considered and examined earlier.

4.6. *Comparison between MPNN and bivariate correlation analyses*

In this study, both MPNN analysis and bivariate correlation analysis demonstrated the importance of factors that can stratify risk. The MPNN model in this study demonstrated a novel approach for evaluating border-fall-related extremity fracture and complications. The limitation of traditional bivariate correlation analysis for identifying stratified multiple risk factors is that it is not able to include other related factors such as demographic variables for integrating analysis. The MPNN model has an ability to take multiple variables into a network simultaneously during analysis and offer the normalized importance to aid in clinical diagnosis.

4.7. *Artificial intelligence (AI) and ML application prospects in medical research*

AI and ML represents the fourth industrial revolution and the next frontier in medical care [26,27]. Through understanding of the fundamental principles and applications of AI in medical science, the power of a ML predictive model to improve patient outcomes has been demonstrated [28]. ML predictive models have been utilized in quality improvement initiatives in older adult's falls[28] and emergency care to reduce complications as well as costs [29–31]. The accuracy of prediction distinguishes ML models from prior retrospective studies utilizing conventional statistical methods [32,33].

Our research efforts have been devoted to the implementation of AI in orthopaedic surgery, sports medicine, and rehabilitation. Together with report in the literature, AI and ML in our research have demonstrated great promise in foreseeing athlete injury risk, interpreting advanced imaging [34], myoelectrical signal processing for robotic assistive rehabilitation [35–37], computer vision and ML-based gait pattern recognition for flat fall prediction [38], evaluating patient-reported outcomes, reporting value-based metrics, and augmenting the patient experience [27].

4.8. Limitations of this study

The limitations of this study is that only MPNN is utilized in the study, other ML methods such as the support vector machines (SVM) [39] or convolutional neural networks (CNN) [35,40,41] have not been investigated to identify if there is a better ML algorithm for building a ML model. The sample size appeared to be small. The appropriate sample size for an MPNN modeling is still controversial. Normally large datasets are necessary to achieve a solid algorithm. However, it has been reported that a sample size of 86 for MPNN can generate excellent machine learning predictive model with an accuracy higher than 91.56 % [42].

4.9. Future studies

We will compare different ML classifiers such as logistic regression (LR) which fits better for dichotomous data [43,44], K nearest-neighbor (KNN) [45,46], Linear Discriminant Analysis (LDA) [45,47,48], support vector machine (SVM) [49–51], and CNN [40,41] to determine if there is a better predictive ML model.

We will build a predictive model for other anatomical injuries including head, chest, abdomen injuries.

5. Conclusions

The study represented a useful application of MPNN ML in trauma research specific to border falls with the potential to improve preoperative diagnosis of extremity fracture and potential complications.

Disclosure of interest

The authors declare that they have no conflict of interest.

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CRediT authorship contribution statement

Carlos Palacio: Writing – review & editing, Supervision, Resources, Project administration, Methodology, Conceptualization. **Maximillian Hovorka:** Resources, Data curation. **Marie Acosta:** Resources, Data curation. **Ruby Bautista:** Resources, Data curation. **Chaoyang Chen:** Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **John Hovorka:** Writing – review & editing, Supervision, Resources, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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