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Analyzing patterns of injury in occupational hand trauma focusing on press machines: a registry-based study and machine learning analysis

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Proceeding Paper

Analyzing Patterns of Injury in Occupational Hand Trauma Focusing on Press Machines: A Registry-Based Study and Machine Learning Analysis [†]

Sarthak Pattnaik ¹, Parita Danole ¹, Sagar Mandiya ¹, Ali Foroutan ², Ghazal Mashhadiagha ¹, Yousef Shafaei Khanghah ², Khatereh Isazadehfar ³ and Eugene Pinsky ^{1,*}

¹ Department of Computer Science, Metropolitan College, Boston University, Boston, MA 02215, USA; spattna1@bu.edu (S.P.); pdanole@bu.edu (P.D.); smandiya@bu.edu (S.M.); mashhadi@bu.edu (G.M.)

² Shiraz University of Medical Sciences, Shiraz 71348-14336, Iran; aliforoutanplastic@gmail.com (A.F.); dr.yousefshafaei@gmail.com (Y.S.K.)

³ Ardabil University of Medical Sciences, Ardabil 56189-53141, Iran; isazadehfar@gmail.com

* Correspondence: epinsky@bu.edu

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Abstract: Objectives: The aim of the project is to analyze the data of patients who have been admitted to the emergency room due to severe hand and palm injuries. Methods: we have used data visualization and statistical analysis to observe trends in various factors pertaining to the patients, such as place of injury, machine-causing injuries, date and time of the injury, amputation, fracture, etiology, distribution of the injured hand, etc. Results: There is a significant difference between age and gender groups across various injuries. Most of the injuries in the dataset are occupational injuries caused by press machines. Most injuries take place in the later half of the week, on Wednesdays and Saturdays. Conclusion: There were 1676 patients who reported to the medical emergency center. Of these, only a handful of them have undergone extremely painstaking injuries where there was uncontrolled bleeding and hemi-amputation. We can also surmise the same by looking at the data that provides the summary of the number of fingers injured. Most patients have either one or two fingers injured. Very few patients had more than two fingers injured.

Keywords: hand trauma; occupational injury; press machine injury; trauma registry; artificial intelligence



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1. Introduction

Hand injuries mostly happen in young men who are economically active and can cause severe disabilities, leading to job loss and the need for long-term rehabilitation. The hand trauma registry comprises detailed information on patterns of injury in trauma patients admitted to an emergency room. Analyzing the information related to the demography of patients and patterns of injury can help us understand the burden and possible mechanism of injury. This can be applied to possible preventive measures. By gaining deeper insights into the underlying causes and trends associated with hand injuries, medical organizations can implement proactive measures to ensure the safety and well-being of patients while at work. Through a comprehensive exploration of the hand trauma registry dataset, this research endeavors to contribute to the advancement of injury prevention strategies, ultimately promoting a safer environment for individuals at risk of severe hand injuries. The data analyzed here is based on four months of recorded data in our registry with 1675 patients in Fatima Hospital in Tehran, Iran. Among occupational injuries, we found that non-standard press machines are commonly responsible for severe hand injuries. We focused on the pattern of injury, and interviewed patients with press machine injuries to understand the burden and mechanism of trauma. This can possibly help health policymakers to decide on preventative measures for such destructive injuries.

2. Methodology

The most critical phase of our project involves meticulously crafting a set of questions that will serve as the guiding outline for our analysis. By structuring our exploration of clinical data around these well-defined questions, we aim to identify trends in the characteristics and extract invaluable insights, which are crucial for the broader scope of the use case. Our primary focus is formulating problem statements that will enable us to curate plausible precautionary measures and effective therapeutic treatments for severe injuries. These areas are of significant interest to medical firms heavily invested in enhancing medical care. Our investigation revolves around two primary datasets: the patients dataset, containing comprehensive details of patients admitted to the emergency room, and the press machines dataset, specifically capturing the history of injuries incurred due to mishandling of press machines. Throughout the analysis, we recognize the paramount importance of key features that underpin our research. These features play a pivotal role in providing valuable insights into injury patterns and characteristics, empowering us to draw meaningful and data-driven conclusions. These features include: age, sex, marital status, hand dominance, presence of amputation and hemi-amputation, cause of accident, type of job, machine causing the injury, anatomy of injury, and date and time of injury.

For patients with a press machine injury, we called the patients and interviewed them about the details of the injury, including: the details of the event, whether they lost their job after injury, costs of treatment, type of job insurance, and calculating the severity of injury using the DASH score.

3. Results

We summarize our main findings:

1. **Day of the Injury:** Most injuries took place on Saturday, followed by Wednesday.
2. **Interval of the day:** Most injuries took place during afternoon hours.
3. **Time of the accident:** The maximum number of accidents occurred between 12 p.m. and 3 p.m.
4. **Place of the accident:** We observe that most of the accidents have occurred at the work-place of these patients, followed by home. In comparison, there is an infinitesimally small number of accidents in other places.
5. **Causes of injury:** The majority of these accidents are occupational in nature, followed by accidental injuries.
6. **Machines causing injuries:** Figure 1 shows the machines that have caused injuries in patients. Saws and press machines are the leading cause of injuries.

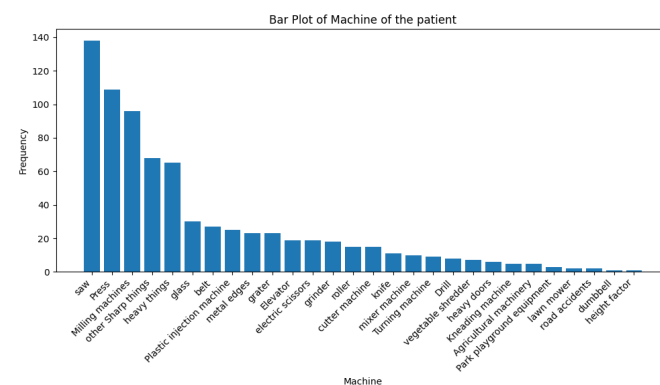


Figure 1. Distribution of the frequency of accidents against machines that have caused injuries.

7. **Occupational injury:** Most occupational injuries took place on a Saturday and in the afternoon hours from 12 P.M. to 6 P.M. For press machine injuries, most of them took place on Wednesday and during morning hours.
8. **Marital status:** Approximately 59% of the patients who are admitted to the hospital are married, and 41% of them are single.
9. **Main occupation:** In total, for 89% of the patients, the occupations were their main occupation, while for the other 11%, the occupation was not their main one.
10. **Dominant hand:** A total of 92% of the patients are right-handed, while 8% of the patients are left-handed.
11. **Hand amputation:** In the patient data, 76% of the patients did not have amputations for their hand injuries, while 24% of patients had amputations.
12. **Uncontrolled bleeding:** Only 5% of the patients who have been admitted to the hospital have experienced uncontrolled bleeding.
13. **Total fingers injured:** Figure 2 shows a comparative study of the percentage of the total number of fingers injured for all accidents and press machine injuries, respectively.

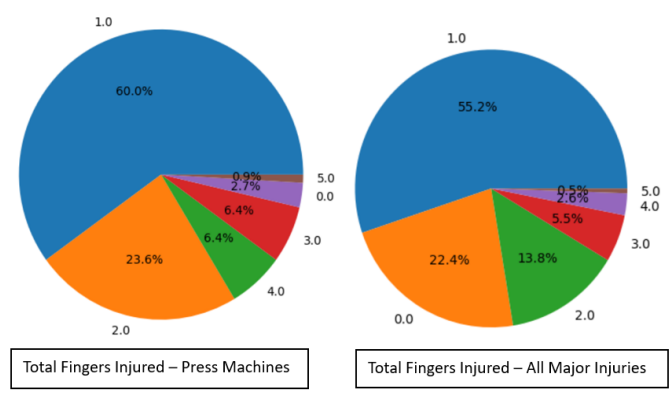


Figure 2. Comparison of total fingers due to press machine against injuries caused due to other machines.

14. **Injured hand:** A total of 49.4% of the patients suffered injury in their right hand, while 49.4% of the patients suffered injury in their left hand. The remaining 1.2% of the patients suffered injury in both hands.
15. **Gender analysis:** Let us explore some key characteristics present in our dataset, focusing on gender differences. Analyzing the distribution of these attributes between males and females could yield intriguing findings and valuable insights.
 - **Gender distribution:** In our ER dataset, 88% of the population is male and only 12% female.
 - **Marital status by gender:** For males, 47% of the patients are single, and 53% of the patients are married. For females, 40% of the patients are single, and 60% of the patients are married. Based on the above results, it is evident that the percentage of married patients is higher compared to unmarried ones. This trend is consistent across both genders. These findings are highly significant, as such injuries impact not only the patients' lives, but also have far-reaching effects on their families as a whole.
 - **Place of accident:** Most men were injured at the workplace, whereas most women were injured at home. Figure 3 illustrates the distribution of places where the injury took place for both genders.
 - **Cause of accidents by marital status:** The proportion of single women who die by suicide is equal to twice the proportion of married women who die by suicide (p value = 0.278). The proportion of single women who die by homicide is equal to twice the proportion of married women who die by homicide (p value = 0.364).
 - **Injured fingers:** Considering all machines, 22% of patients injured their first finger, 30% injured their second finger, 25% injured their third finger, 20% injured their fourth finger, and 14% injured their fifth finger. For press machine injuries,

25% of patients injured their first finger, 55% of the patients injured their second finger, 39% of the patients injured their third finger, 24% of patients injured their fourth finger, and 12% of patients injured their fifth finger.

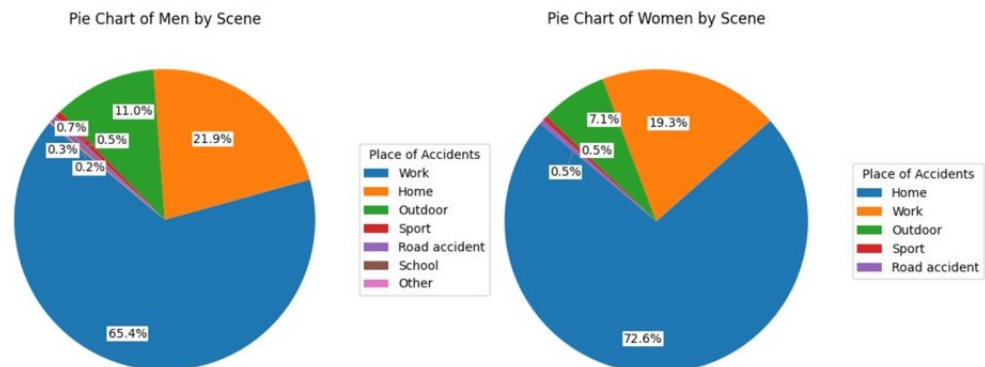


Figure 3. Place of accidents for males and females.

16. **Press machines:** The press machines dataset consists of 112 records. The visualization charts below show results obtained after a thorough analysis of the dataset.
- **Age of patients:** The highest number of patients who were admitted to the hospital belong to the age groups of 16–20 and 25–35. This is illustrated in Figure 4.
 - **Distribution of injured hand:** In total, 94% of the patients of the patients are right-handed and 6% of the patients are left-handed. A total of 53.6% of the patients injured their right hand, 42% of the patients injured their left hand, and 4.5% of the patients injured both of their hands.
 - **Etiology:** In total, 43% of the etiology is caused by device failure, 37.5% of the etiology is caused by carelessness, 15.3% of the etiology is caused by lack of experience, 2.8% is caused by the mistakes of others, and 1.4% is caused by the failure to install the device.
 - **Fracture:** A total of 64.5% of the patients who encountered fractures had injuries in their phalanx. The other patients incurred injuries in the wrist, ulna, radius, metacarp, and phalanx.
 - **Types of fracture:** In total, 65.5% of the patients encountered comminuted fractures, whereas 1.8% of the patients suffered linear fractures.
 - **Joint injuries:** A total of 32% of the patients had injuries in their DIP, 5.8% of patients injured the PIP, 4.9% of the patients injured the MCP, 4.9% of patients injured both PIP and DIP, and 1% of patients injured their carpal.
 - **Flat Coverage:** The flat coverage distribution consists of 33% stump, 8.3% advancement, 6.4% graft, and the remaining 4.5% comprises the inguinal flap, composite draft, fasciotomy, inguinal, and dorsum.
 - **Extra injuries:** In total, 77.1% of the patients had no extra injuries, 17.1% of the patients had one extra injury, and 5.7% of patients had two extra injuries.
 - **Change in job:** A total of 50% of the patients who had an injury due to a press machines changed their jobs.
 - **Job absence:** In total, 37.5% of the patients took two days leave, 31.9% of patients took one day of leave, and 18.1% of the patients took three days of leave.
 - **Severity of injury:** We will use the DASH score to predict the severity of the injury. This is illustrated in Figure 5.

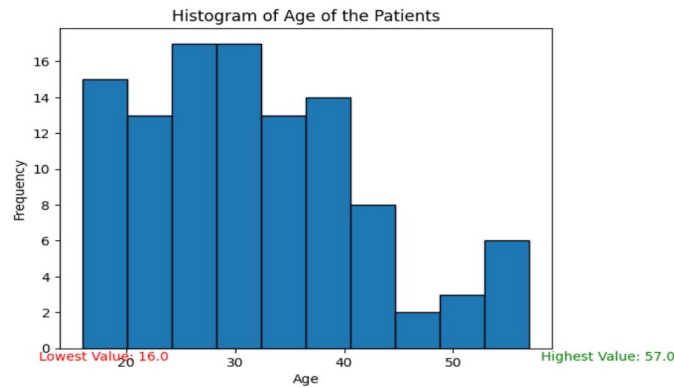


Figure 4. Age of patients who have been admitted in the hospital.

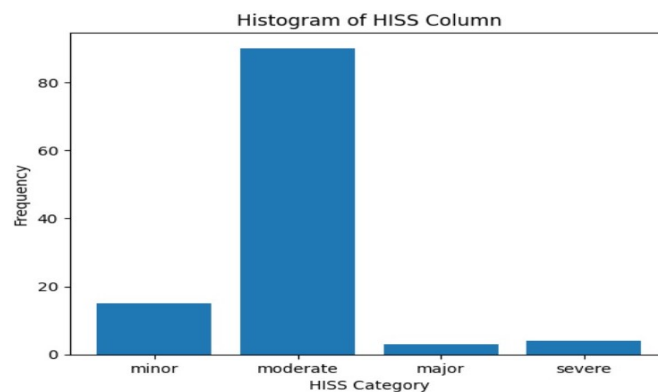


Figure 5. DASH category.

4. Insights Using Machine Learning

Machine learning algorithms are invaluable assets for medical professionals dealing with patients who have undergone hand trauma. These algorithms, including Logistic Regression and Random Forest models, offer crucial insights into patient data, deciphering complex patterns within demographic variables, temporal features, and medical indicators. Such deep analysis facilitates personalized risk assessment, enabling healthcare providers to identify individuals at higher risk of complications, such as amputation. Early detection and intervention are made possible through these models, allowing medical practitioners to address potential issues before they escalate, leading to improved patient outcomes. Studies by Hastie et al. (2009) [1] and Breiman (2001) [2] underscore the robustness of machine learning methodologies in medical contexts, emphasizing their role in enhancing decision-making processes and enabling tailored treatment strategies. By harnessing the power of machine learning, healthcare professionals can deliver targeted and efficient care, ultimately enhancing the quality of healthcare services for individuals recovering from hand trauma.

5. Results Obtained from Machine Learning

The findings from our study, utilizing machine learning techniques such as Logistic Regression and Random Forest models, offer valuable insights into predicting the risk of amputation in patients recovering from hand trauma. To put it simply, these models help us understand how accurately we can assess this risk. In the Logistic Regression model, we observed a precision of 67% for one group of patients (Group A), and 79% for another group (Group B) as documented in Tables 1 and 2. This means that when the model indicated a risk of amputation, it was correct 67% of the time for Group A and 79% for Group B. However, it made errors as well. For some patients in Group A, it indicated a risk when there was not one 33% of the time, and for some patients in Group B, it missed the risk 21% of the time. On the other hand, the Random Forest model performed

better as seen in Tables 3 and 4. It accurately identified patients at risk 80% of the time for Group A and 82% for Group B, making fewer mistakes than the Logistic Regression model. These results are in line with recent advancements in machine learning techniques applied to medical contexts [3]. Our study contributes to this growing body of knowledge, emphasizing the importance of accurate risk assessment in patient care. The Random Forest model, in particular, stands out as a promising tool for medical professionals, offering a reliable method to identify patients at risk of amputation after hand trauma [4]. This progress signifies a significant step forward in providing targeted and effective care for these patients, ensuring they receive timely interventions and support.

Table 1. Confusion matrix obtained from Logistic Regression model.

TP	TN	FP	FN
15	2	4	1

Table 2. Reults obtained from Logistic Regression model.

Label	Precision	Recall	f1-Score	Support
0	0.67	0.33	0.44	6
1	0.79	0.94	0.86	16

Table 3. Confusion matrix obtained from Random Forest model.

TP	TN	FP	FN
14	4	3	1

Table 4. Results obtained from Random Forest model.

Label	Precision	Recall	f1-Score	Support
0	0.67	0.33	0.44	6
1	0.79	0.94	0.86	16

6. Differences between Groups

We used a method called hypothesis testing, specifically the chi-square test, to carefully look at the differences between the different genders and marital statuses among our patients. This statistical technique helps us understand if there are significant differences in outcomes based on these factors. In simpler terms, imagine that we have different groups of patients based on their gender (male, female, other) and marital status (single, married, divorced, widowed). We wanted to see if these factors affect certain aspects of patient outcomes. The chi-square test helps us figure this out by comparing the data we observed with what we expect to see by chance. We set a significance level of 0.05, which means we are 95% confident in our results. If the differences we found are larger than we would expect by random chance (according to the chi-square test), we can say these differences are significant. The results of our tests, shown in Table 5, tell us important things about how gender and marital status might influence patient outcomes. This analysis gives us a better understanding of our patients and helps us provide more personalized and effective care [4]. In our study, we conducted several tests to understand how different factors relate to accidents. We looked at gender groups and marital statuses in relation to various aspects like the causes of accidents, where accidents happened, types of jobs, and machines used. The results tell us if there are significant connections between these factors. For gender groups, we found strong evidence (p value < 0.05) indicating that the type of accidents, the places they occur, and the jobs involved are indeed related to gender [5]. This means that gender plays a role in the nature of accidents. However, the specific machines used

didn't show a strong correlation with gender [6]. When it comes to marital status, we discovered that it influences the causes of accidents and the locations where they happen. Marital status didn't have a significant impact on the type of jobs people were doing or the machines they were using. In simpler terms, our tests show that gender and marital status affect the circumstances of accidents in specific ways. This information is valuable for medical professionals because it helps us understand the patterns and factors associated with accidents. By knowing these connections, we can potentially take preventive measures and provide better care to patients based on their specific situations.

Table 5. Summary of statistical tests.

Comparison	<i>p</i> Value
Gender Groups vs. Cause of Accidents	≤0.05
Gender Groups vs. Place of Accidents	≤0.05
Gender Groups vs. Types of Jobs	≤0.05
Gender Groups vs. Machines Used	0.096
Marital Status vs. Cause of Accidents	0.0017
Marital Status vs. Place of Accidents	0.005
Marital Status vs. Types of Job	≤0.05
Marital Status vs. Machine Used	0.94

7. Discussion

The comparison of our research findings with existing literature illuminates a consistent alignment with global trends in hand injury epidemiology. Several studies have underscored the prominence of hand injuries among young, economically active males, a demographic pattern strikingly mirrored in our dataset [7–10]. This demographic consistency underscores the universal challenge faced by diverse industries, where the workforce predominantly comprises young men, rendering them more susceptible to occupational hazards. Notably, the prevalence of occupational injuries due to machinery, especially non-standard press machines, resonates with prior research conducted across different regions and industrial sectors [7,11,12]. Smith and Johnson's study emphasized the significance of identifying and prioritizing prevention targets, focusing on machinery-related injuries, aligning seamlessly with our observation that saw and press machines were primary causes of injuries [7].

The temporal patterns of hand injuries, including specific days and hours of higher incidence, have been extensively studied across various contexts. Lee et al.'s decade-long analysis of hand injuries in Northern Ireland elucidated temporal shifts and patterns within the region, corroborating our findings regarding higher injury rates on Saturdays and during afternoon hours [9]. This correspondence suggests the importance of targeted safety measures and staff deployment during these periods to mitigate injury occurrences effectively.

Gender disparities in hand injuries have been a recurring theme in the existing literature, with distinctive injury patterns observed among males and females [10,13]. Meyers and Wang's studies in New Jersey underscored the significance of analyzing age- and gender-specific differences in occupational hand injuries, aligning with our study, which demonstrated a higher prevalence of injuries among males, especially in workplace settings [13].

Furthermore, Scott and Stone's qualitative study delved into the socio-economic impact of hand injuries, providing invaluable insights into the personal and economic consequences experienced by affected individuals and their families [14]. Conducting similar in-depth analyses could offer a comprehensive understanding of the multifaceted implications of hand injuries, thereby informing holistic interventions and support systems.

Machine learning applications in injury prediction have gained prominence, transforming the field of injury prevention [15]. Tavakoli and Khatibi's research demonstrated the efficacy of machine learning models for predicting hand injury outcomes, resonating with our use of machine learning techniques, particularly logistic regression, to discern

predictive factors influencing injury severity, amputation, and accident scenes [15]. Press machines can cause devastating injuries, including severe soft tissue injuries and multi-fragmented fractures. Press machines should have a sensor to cause a stop if the hand of the worker is going to be compressed in the machine.

In conclusion, our study not only reaffirms the established trends in hand injury epidemiology, but also enriches the field with specific insights into non-standard press machine-related injuries, temporal patterns, and gender-specific injury disparities. Drawing on this rich body of literature, our findings underscore the urgency for tailored workplace safety regulations, enhanced training programs, and focused policy interventions. These measures align with global efforts to reduce the burden of hand injuries and ensure safer working environments for all employees.

8. Conclusions

This study provides a deep dive into severe hand injuries, shedding light on workplace safety concerns, notably concerning non-standard press machines. This research emphasizes the urgency of implementing tailored safety protocols, particularly during specific times and days, and for specific types of machines. Furthermore, it offers crucial insights into the broader societal and economic impact of hand injuries, highlighting the necessity for holistic preventive strategies. These strategies should encompass rigorous workplace regulations, comprehensive safety training programs, and targeted policy interventions. By addressing these key areas, we can pave the way for a safer work environment and, subsequently, a healthier, more productive society.

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