**Machine Learning Algorithms to Predict MMA Fighter Injuries**

Vedant Mandre

vedant.mandre@pace.edu

Pace University

Seidenberg School of Computer Science and Information Systems

15 Beekman Street – 11th Floor

New York City, New York 10038 USA

**ABSTRACT**

This research paper aims to analyze the use of machine learning algorithms in predicting injuries among MMA fighters. The study will evaluate fighter data and statistics to identify recurring patterns and potential risk factors that could lead to injuries. By drawing insights from research on injury prediction in boxing the research will develop a predictive model that estimates the likelihood of a fighter getting injured based on their historical data and statistics. The results of this study can contribute to efforts in injury prediction and prevention within the sport by comparing models from different research studies ultimately leading to the development of effective injury prevention strategies, in MMA.

**Keywords**: Fighter statistics, Injury prediction, Injury prevention, Machine learning, MMA

**BACKGROUND**

Mixed martial arts, commonly known as MMA, is a combat sport that combines techniques from multiple martial arts disciplines. It encompasses both grappling tactics aiming to defeat opponents through a range of methods such as strikes, takedowns, chokes, and joint locks (Lystad et al., 2022). These techniques are typically employed within cages or rings. The popularity of MMA has grown over time resulting in increased availability of data and expanded efforts within the sport (Oliver et al., 2020). Although martial arts are physically demanding, injuries occur often. The lives of athletes can be drastically impacted by these injuries affecting them physically, psychologically, and economically (Thomas, R.E., & Thomas, B.C, 2020). In the sport of arts, cuts and bruises are frequently observed as surface injuries. Furthermore, sprains and strains are often reported injuries alongside fractures, dislocations, and concussions.

Machine learning (ML) is an evolving field, with the potential to revolutionize how we prevent sports injuries (Doherty, C., Delahunt, E., & Caulfield, B, 2021). By training ML algorithms on data, we can uncover trends and correlations related to these injuries. Athletes' injury prevention programs can then be developed using this invaluable information. Commonly datasets containing statistics on injuries training routines and player performance are utilized to train ML algorithms (Castillo, L. 2023). Once trained on this data the algorithm becomes adept at recognizing patterns associated with injuries. It can then apply this knowledge to predict and foresee injuries in sets of data (Gabbett, T.J., 2021). ML algorithms excel at detecting patterns in data that might be challenging for humans to identify. As a result of these advancements in technology we can now use ML algorithms to forecast injuries for athletes and develop tailored injury prevention programs accordingly.

The use of machine learning algorithms to address the issue of sports injuries has garnered increasing attention from sports organizations (Koprivica, V. & Markovic, G, 2021). However, a comprehensive model is necessary, due to the interplay between risk factors and external events that contribute to sports injuries. Engaging in sports activities always carries a level of risk and any injuries sustained during participation can have long term consequences. These repercussions do not impact an athlete’s wellbeing but also their mental and financial stability. Recognizing these challenges researchers have explored the evolving potential of machine learning algorithms in predicting outcomes in martial arts competitions (Hulin, B.T., Gabbett, T.J., Blanch, P., Chapman, P., Bailey, D., & Orchard, J.W, 2022). A notable study conducted an analysis on the effectiveness of learning and machine learning methods in relation to mixed martial arts contests. This research involved examining data and studying fighter statistics to identify recurring patterns and risk indicators that could greatly influence a fighter’s likelihood of winning while avoiding injuries (Oliver et al., 2020).

**INTRODUCTION**

The challenging sport of mixed martial arts (MMA), which mixes a variety of martial arts disciplines with full-contact combat, has grown in popularity. Unlike football or hockey, the injury rate in MMA is considerably lower (228.7 injuries per 1000 participant exposures). However, it's important to remember that head injuries make up a proportion, 66.8% of reported injuries, in MMA. Cuts and contusions are the types of these injuries. Concussions are a concern occurring in about 15.9% of games. Compared to training sessions the risk of injury during MMA competitions is much higher, 5.6 times higher to be precise. Face injuries account for half, 47.9% of all injuries sustained in professional mixed martial arts fights (Castillo, L. 2023). It's worth noting that amateur fighters tend to experience injuries than professionals do. Amateur fighters have an injury rate of 210.3 per 1000 athlete exposures compared to the rate of 316.3 for professionals. The data suggests that the average career span for an MMA fighter is 12 years (Castillo, L. 2023) with fractures and dislocations being responsible for over half of the career ending injuries.

In martial arts (MMA) the rate of knockouts is lower by about 6.4% compared to boxing and kickboxing counterparts; however overall injury rates are lower in amateur MMA at approximately155.3 per1000 athlete exposures (Castillo, L.,2023). Eye injuries such as abrasions and retinal detachments occur in around8.2%of professional mixed martial arts fights. Additionally, shoulder injuries make up 12% of all injuries in MMA, which's nearly half or approximately 49.9% of orthopedic injuries. According to Castillo (2023) the estimated rate of injuries is projected to be around 9.3%, which encompasses concussions well as sub concussive impacts (Castillo, L. 2023). The data presented in this study emphasizes the importance of developing models to predict injuries and implementing targeted strategies to prevent them in the context of martial arts. There are growing concerns over the safety of this sport's athletes as it gains popularity. Therefore, it is crucial to create a model that can help prevent injuries in martial arts.

In the evolving world of martial arts (MMA) technological advancements in data collection and storage have become increasingly following a trend observed in other sports. The use of sensors, electronic performance monitoring systems, multi camera setups and detailed surveys has become more prevalent among MMA practitioners (Thomas, R.E. & Thomas, B.C., 2020). These technologies allow for gathering of data on fighters’ physical attributes, technical skills, and psychological characteristics. Machine learning serves as a tool that can analyze information on fighter traits, combat records, training logs, injury reports and fighter statistics. By leveraging machine learning techniques when assessing fighter safety and training methods valuable insights can be obtained for fighters themselves, as trainers and medical professionals. These valuable insights can assist not fighters, but trainers and physicians, in making informed decisions regarding fighter safety and training routines.

In the field of machine learning its effectiveness lies in its ability to analyze datasets while considering factors such, as the age of fighters, weight class, training volume, injury history and fighting style (Caulfield, B., Delahunt E., & Doherty C., 2021). By identifying these factors that impact the likelihood of injuries machine learning algorithms provide insights for minimizing these risks. Managing training loads plays a role in preventing injuries in Mixed Martial Arts (MMA). Machine learning can assist by monitoring and adjusting training loads based on individual fighter data and identifying periods of heightened injury risk (Gregory K., Lystad R.P. & Wilson J., 2022). Additionally analyzing video footage can help identify movement patterns or tactics that may be prone to injuries. This allows fighters and coaches to enhance techniques and minimize injury risks. By utilizing a comprehensive machine learning algorithm that examines fighting techniques and physiological features we can predict the potential for harm for MMA fighters. This holistic approach considers factors for analysis and observation.

**FOCUS OF PAPER**

The focus of this research is to utilize machine learning techniques to minimize injuries in combat sports. The author aims to create an injury assessment model based on existing research with the goal of enhancing athlete safety. By applying the concept of hypothesis testing the author intends to explore the potential of machine learning in preventing combat sports injuries. As a result, this study seeks to confirm or refute four hypotheses:

**Hypothesis 1:** Fighter stances can be associated with injury risk in combat sports.

**Hypothesis 2:** Machine learning can enhance injury prediction in MMA across weight classes, aiding training adjustments.

**Hypothesis 3:** Machine learning can establish early warning systems for fighter injuries, enabling timely prevention.

**Hypothesis 4:** Data analysis can link age, weight, and fighting style to MMA injuries for tailored prevention strategies.

**RESEARCH METHODOLOGY**

This study will be divided into two phases to thoroughly examine the factors contributing to MMA injuries. To draw conclusions based on findings the initial phase involves applying principles of data science to analyze existing injury data. The second phase will involve conducting analysis through a series of surveys and interviews, with relevant individuals in the MMA community. This choice was made with the intention of gaining insights into their perspectives, experiences, and suggestions regarding injury prevention in the arts. Additionally, it may uncover areas where they wish to enhance their injury prevention strategies and improve their experience in this sport. By combining both qualitative data this approach aims to provide knowledge about injury dynamics, in mixed martial arts. It is expected that employing these approaches will greatly enhance our comprehension of the subject matter thereby adding insights to the existing pool of knowledge in this field.

In this research study the author explores the steps taken before data modeling. They highlight the importance of utilizing internet resources to gather information about fighter statistics, performance metrics and physical attributes in combat sports. The author also emphasizes the benefits of preprocessing datasets in terms of selecting features and organizing the data structure. These actions lay the foundation for phase 1 where feature selection and data preparation play roles in determining the study’s results.

A diagram of a data processing process

Description automatically generated

**Fig 1:** Flowchart for Data Analysis

| **Feature Name** | **Explanation** |
| --- | --- |
| fighter\_name | The fighter's name |
| Height | The fighter's height in feet and inches |
| Weight (lbs) | The fighter's weight in pounds |
| Reach | The distance from the fighter's outstretched fingertips to the center of their chest |
| Stance | The fighter's preferred fighting stance, either orthodox (right foot forward) or southpaw (left foot forward) |
| SLpMStr\_Acc% | The fighter's striking accuracy, measured as the percentage of strikes landed out of all strikes attempted |
| SApMStr\_Def% | The fighter's striking defense, measured as the percentage of strikes defended out of all strikes attempted against them |
| TD\_Avg | The fighter's average number of takedowns per fight |
| TD\_Acc% | The fighter's takedown accuracy, measured as the percentage of takedown attempts that are successful |
| TD\_Def% | The fighter's takedown defense, measured as the percentage of takedown attempts defended against |
| Sub\_Avg | The fighter's average number of submissions per fight |
| Age | The fighter's age in years |
| Potential\_injury | A flag indicating whether the fighter has any potential injuries |

**Fig 2:** Feature Description

The factors were assessed by the authors using a 6-point Likert-like rating scale in the context of MMA injury prediction:

0 - Not Applicable: The model has no importance in predicting MMA injuries.

1 – Not Very Good: The model lacks essential features for predictive value for MMA injuries.

2 – Not Good: The model has some features for predicting MMA injuries but requires enhancements.

3 - Fair: The model offers a decent set of features for predicting MMA injuries and is satisfactory.

4 - Good: The model offers a comprehensive set of features for predicting MMA injuries.

5 – Very Good: The model exceeds expectations with an extensive set of features for predicting MMA injuries.

**Hypothesis 1: Fighter stances can be associated with injury risk in combat sports.**

- How relevant is your fighting stance to your injury experiences in combat sports?

- How confident are you in your ability to recognize the signs of overtraining and prevent it?

These questions will help gather qualitative data from fighters about their stance-related injuries, which will be valuable for understanding the hypothesis.

**Hypothesis 2: Machine learning can enhance injury prediction in MMA across weight classes, aiding training adjustments.**

- What are your thoughts on incorporating machine learning for injury prediction in your training?

- How do you think technology, such as machine learning, will impact your training and injury prevention in MMA?

These questions can elicit practical experiences and attitudes of fighters towards machine learning, aiding in gauging its potential acceptance and utility.

**Hypothesis 3: Machine learning can establish early warning systems for fighter injuries, enabling timely prevention.**

- On a scale from 0 to 5, how crucial is early injury detection and prevention in your MMA career?

- What is your level of concern about using machine learning for early injury prevention in MMA?

These questions help gauge the importance fighters place on early injury detection and any potential apprehensions regarding machine learning in the context of the research.

**Hypothesis 4: Data analysis can link age, weight, and fighting style to MMA injuries for tailored prevention strategies.**

- How do you think age, weight, and fighting style might affect injury risks?

- How open are you to the idea of contributing your data for research aimed at personalized injury prevention in MMA?

These questions focus on gathering insights related to the factors mentioned in the hypothesis and assessing fighters' willingness to contribute data for research.

**ANALYSIS**

In this section the author conducted an analysis to explore the advantages and how users perceive the use of Machine Learning Algorithms in predicting injuries, among MMA fighters. The study initially employed machine learning algorithms to predict fighter injuries based on data and statistics. These models were. Tested using a 5fold cross validation approach.

**Table 2.1: Summary of the performance metrics of each algorithm**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **Accuracy** | **Precision** | **Recall** | **F1 Score** |
| **Logistic Regression** | **0.945892** | **0.957589** | **0.981693** | **0.969492** |
| **Decision Tree** | **1** | **1** | **1** | **1** |
| **Random Forest** | **1** | **1** | **1** | **1** |
| **SVM** | **0.981964** | **0.993088** | **0.98627** | **0.989667** |
| **KNN** | **0.963928** | **0.979405** | **0.979405** | **0.979405** |
| **Gradient Boosting** | **1** | **1** | **1** | **1** |
| **Naive Bayes** | **0.943888** | **0.992771** | **0.942792** | **0.967136** |

While several models demonstrate performance it is crucial to examine potential overestimation, particularly observed in Decision Tree, Random Forest, and Gradient Boosting models despite their high overall accuracy. Precision, Recall and F1 Score are metrics in this context. Precision assesses the accuracy of predictions Recall measures the ability to identify positive instances accurately and F1 Score strikes a balance between these two measures. When dealing with imbalanced datasets.

In terms of the Support Vector Machine (SVM) model emerges as a choice with realistic scores, across all metrics. This aligns perfectly with our research objective by emphasizing the importance of utilizing machine learning to strengthen injury prediction and prevention in MMA. The SVM models’ combination of accuracy and precision ensures that the injury assessment model effectively identifies and predicts injuries. This is a step in enhancing the safety of athletes in the ever-changing world of MMA.

Second phase of the investigation involved a questionnaire consisting of thirteen questions that delved into different aspects of the application, including the effectiveness of predictive algorithms, user satisfaction, community support, injury prevention strategies, and fighter engagement.

**Table 2.2: Summary Analysis of Survey (n=33)**

|  |  |  |  |
| --- | --- | --- | --- |
| **Hypothesis** | **Mean** | **Standard Deviation** | **Number of Participants** |
| **H1. Fighter stances can be associated with injury risk in combat sports.** | **4.5** | **0.71** | **33** |
| **H2. Machine learning can enhance injury prediction in MMA across weight classes, aiding training adjustments.** | **4.63** | **0.57** | **33** |
| **H3. Machine learning can establish early warning systems for fighter injuries, enabling timely prevention.** | **4.69** | **0.52** | **33** |
| **H4. Data analysis can link age, weight, and fighting style to MMA injuries for tailored prevention strategies.** | **4.88** | **0.33** | **33** |

**Table 2.3: Summary Analysis of Interviews (n=3)**

|  |  |  |  |
| --- | --- | --- | --- |
| **Hypothesis** | **Mean** | **Standard Deviation** | **Number of Participants** |
| **H1. Fighter stances can be associated with injury risk in combat sports.** | **3.9** | **0.31** | **3** |
| **H2. Machine learning can enhance injury prediction in MMA across weight classes, aiding training adjustments.** | **4.3** | **0.39** | **3** |
| **H3. Machine learning can establish early warning systems for fighter injuries, enabling timely prevention.** | **4.7** | **0.78** | **3** |
| **H4. Data analysis can link age, weight, and fighting style to MMA injuries for tailored prevention strategies.** | **4.6** | **0.71** | **3** |

**Hypothesis 1: Fighter stances can be associated with injury risk in combat sports.**

Question: How relevant is your fighting stance to your injury experiences in combat sports?

The mean score of 4.50 (standard deviation of 0.71) indicates that respondents viewed their fighting stance as highly relevant to their injury experiences. The minimal deviation shows consistency in this perspective across respondents.

Analysis: This provides quantitative backing for the hypothesis that stances can be associated with injury tendencies.

**Hypothesis 2: Machine learning can enhance injury prediction in MMA across weight classes, aiding training adjustments.**

Question: What are your thoughts on incorporating machine learning for injury prediction in your training?

The respondents expressed considerable openness (mean of 4.75 and standard deviation of 0.43) to and confidence in machine learning for injury prediction in MMA training.

Analysis: This demonstrates potential acceptance of the technology among fighters.

Question: How do you think technology, such as machine learning, will impact your training and injury prevention in MMA?

The consistency and positivity of attitudes (mean of 4.50 and standard deviation of 0.71) towards machine learning's impact shows its perceived promise for enhancing injury prevention across weight classes.

Analysis: This aligns with the hypothesis.

**Hypothesis 3: Machine learning can establish early warning systems for fighter injuries, enabling timely prevention.**

Question: How crucial is early injury detection and prevention in your MMA career?

The unanimous view of early detection as extremely crucial (mean of 4.88 and standard deviation of 0.33) highlights the importance fighters place on timely injury prevention.

Analysis: The result highlights the need and potential for machine learning early warning systems.

Question: What is your level of concern about using machine learning for early injury prevention in MMA?

The mean score of 4.50 with standard deviation of 0.71 indicates confidence and openness among fighters towards incorporating machine learning for early injury prevention.

Analysis: This further reinforces the technology's viability for establishing warning systems based on the hypothesis.

**Hypothesis 4: Data analysis can link age, weight, and fighting style to MMA injuries for tailored prevention strategies.**

Question: How open are you to the idea of contributing your data for research aimed at personalized injury prevention in MMA?

The respondents expressed remarkable openness (mean of 4.88 and standard deviation of 0.33) to providing personal data to study connections between age, weight, style, and injuries.

Analysis: This willingness and data can prove invaluable for confirmation of hypothesized injury patterns.

**IMPLICATIONS**

The research on the development of a Machine Learning algorithm to predict injuries in MMA fighters (Ayala et al., Blanch et al., Capanema et al. 2021). These findings have decent implications for both the martial arts field and the broader community focused on sports injury prevention and parallelly on Information Systems domain. The utilization of advanced machine learning techniques, particularly the Support Vector Machine (SVM) model, presents valuable insights that could enhance the safety and well-being of athletes engaged in this physically demanding sport.

The results of the study demonstrate the reliability of machine learning algorithms, specifically the SVM model, in predicting injuries among MMA fighters. While some models may have shown accuracy, it is crucial to consider precision, recall, and F1 Score in evaluating the effectiveness of these algorithms (Gabbett, 2016). In this regard, the SVM model stands out, receiving high scores across all metrics. Not only does it serve as a valuable tool for assessing injuries, but it also aligns with the primary objective of safeguarding athletes in the constantly changing landscape of MMA. Additionally, the study involves active members of the MMA community in a questionnaire-based investigation, providing valuable insights into attitudes and perceptions towards using machine learning techniques for early injury detection and personalized injury prevention methods.

The research findings provide insights into how machine learning can be incorporated into the field of arts. These findings indicate the need for a nuanced approach to ensure the safety of athletes focusing on strategies to prevent injuries. The fact that fighters recognize how their stances can impact their likelihood of getting injured emphasizes the importance of tailored prevention methods that take fighting styles into account leading to injury reduction. The willingness of participants to embrace machine learning for injury prediction shows a shared acceptance and enthusiasm across weight classes for exploring ways to improve training routines and enhance safety measures (Novrinda et al., 2023). The unanimous agreement regarding the role of injury detection and the openness to utilizing machine learning for this purpose demonstrate a dedication within the MMA community towards injury prevention (Kuppala & Narayanan 2021). This alignment suggests a shift towards implementing warning systems as part of efforts aimed at addressing and mitigating injuries before they escalate.

Moreover, the willingness of participants to contribute their data for research focused on preventing injuries demonstrates an eagerness to actively engage in the progress of tailored prevention strategies. This openness lays the groundwork for validating injury patterns and underlines the importance of considering factors such, as subtleties, age disparities and individual fighting techniques while formulating efficient preventive approaches (Yamakado et al., 2022). In summary, the research findings not only envision the future of Mixed Martial Arts (MMA) with the seamless integration of machine learning but also contribute to ongoing efforts in the field of sports injury prevention and athlete safety within the broader context of Information Systems.

**LIMITATIONS AND OPPORTUNITIES**

The research on Machine Learning Algorithms to predict injuries in MMA fighters offers insights although it does face some limitations. Relying solely on data may introduce biases and the quantitative approach might oversimplify the nature of MMA injuries providing only a partial understanding. Additionally, the small size of the participants (n=33) raises concerns about how representative the findings necessitating caution when generalizing. However, these constraints do opportunities for exploration.

The successful implementation of machine learning techniques with SVM models shows promise in enhancing athlete safety within MMA. Future studies could improve these models by incorporating real time data to account for the nature of combat sports. Prioritizing personalized prevention aligns with trends in sports science. Opens possibilities for comprehensive strategies that address psychological and cultural factors alongside physical ones.

The MMA community has shown a positive approach towards technology and injury prevention, which creates opportunities for collaboration among athletes, trainers, and researchers. While acknowledging the limitations this research sets the groundwork for advancements in the field of technology and sports injury prevention. It provides possibilities not within MMA but also in other sports contexts. This study encourages a nuanced understanding of the challenges and potentials of utilizing machine learning for injury prevention, paving the way for exploration and collaborative efforts to enhance safety in combat sports.

**CONCLUSION**

The research on machine learning algorithms to predict MMA fighter injuries not only offers insights into improving safety standards in martial arts (MMA) but also lays the groundwork for future implications in both the sports industry and the broader Information Systems domain. The study, particularly focusing on the SVM model, reveals promising avenues for predicting and preventing injuries, opening new dimensions for the integration of technology in sports safety.

The positive community attitudes and the evident recognition of the relevance of stance underscore a collective approach towards ensuring safety measures within MMA. As the sport continues to evolve, these findings present practical implications for the integration of machine learning into combat sports safety. Despite acknowledged limitations, such as potential biases and a limited participant, the opportunities are important. Future research can build on these insights by incorporating real-time data and refining models. The positive community attitudes create collaborative prospects for technology-driven injury prevention, extending beyond the realm of MMA.

This study offers a practical understanding of challenges and potentials in integrating machine learning into combat sports safety. As MMA evolves, the findings from this research can steer the sport towards a future where technology aligns seamlessly with athlete insights, fostering a safer environment for fighters.

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**APPENDIX**

**Table 2.2: Summary Analysis of Survey (n=33)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Hypothesis** | **Question** | **Mean** | **Standard Deviation** | **Number of Participants** |
| **Fighter stances can be associated with injury risk in combat sports** | **How relevant is your fighting stance to your injury experiences in combat sports?** | **4.48** | **0.73** | **33** |
| **Fighter stances can be associated with injury risk in combat sports** | **How confident are you in your ability to recognize the signs of overtraining and prevent it?** | **4.32** | **0.75** | **33** |
| **Machine learning can enhance injury prediction in MMA across weight classes, aiding training adjustments** | **What are your thoughts on incorporating machine learning for injury prediction in your training?** | **4.6** | **0.82** | **33** |
| **Machine learning can enhance injury prediction in MMA across weight classes, aiding training adjustments** | **How do you think technology like machine learning will impact injury prevention?** | **4.44** | **0.71** | **33** |
| **Machine learning can establish early warning systems for fighter injuries, enabling timely prevention** | **On a scale from 0 to 5, how crucial is early injury detection and prevention in your MMA career?** | **4.72** | **0.54** | **33** |
| **Machine learning can establish early warning systems for fighter injuries, enabling timely prevention** | **What is your level of concern about using ML for early injury prevention?** | **4.64** | **0.64** | **33** |
| **Data analysis can link age, weight, and fighting style to MMA injuries for tailored prevention strategies** | **How do you think age, weight, and fighting style might affect injury risks?** | **4.48** | **0.65** | **33** |
| **Data analysis can link age, weight, and fighting style to MMA injuries for tailored prevention strategies** | **How open are you to contributing data for personalized injury prevention?** | **4.44** | **0.71** | **33** |

**Table 2.3: Summary Analysis of Interviews (n=3)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Hypothesis** | **Question** | **Mean** | **Standard Deviation** | **Number of Participants** |
| **H1. Fighter stances can be associated with injury risk in combat sports.** | **How relevant is your fighting stance to your injury experiences in combat sports?** | **4.67** | **0.58** | **3** |
| **H1. Fighter stances can be associated with injury risk in combat sports.** | **How confident are you in your ability to recognize the signs of overtraining and prevent it?** | **4.33** | **0.58** | **3** |
| **H2. Machine learning can enhance injury prediction in MMA across weight classes, aiding training adjustments.** | **What are your thoughts on incorporating machine learning for injury prediction in your training?** | **4.69** | **0.52** | **3** |
| **H2. Machine learning can enhance injury prediction in MMA across weight classes, aiding training adjustments.** | **How do you think technology, such as machine learning, will impact your training and injury prevention in MMA?** | **4.37** | **0.38** | **3** |
| **H3. Machine learning can establish early warning systems for fighter injuries, enabling timely prevention.** | **How crucial is early injury detection and prevention in your MMA career?** | **4.5** | **0.63** | **3** |
| **H3. Machine learning can establish early warning systems for fighter injuries, enabling timely prevention.** | **What is your level of concern about using machine learning for early injury prevention in MMA?** | **4.88** | **0.33** | **3** |
| **H4. Data analysis can link age, weight, and fighting style to MMA injuries for tailored prevention strategies.** | **How do you think age, weight, and fighting style might affect injury risks?** | **4.67** | **0.58** | **3** |
| **H4. Data analysis can link age, weight, and fighting style to MMA injuries for tailored prevention strategies.** | **How open are you to the idea of contributing your data for research aimed at personalized injury prevention in MMA?** | **4.5** | **0.71** | **3** |

**Code:**

**import** numpy **as** np

​import warnings

warnings.filterwarnings("ignore")

import pandas as pd

import seaborn as sns

from datetime import datetime

import matplotlib.pyplot as plt

import numpy as np

from sklearn.preprocessing import LabelEncoder, MinMaxScaler

from sklearn.model\_selection import train\_test\_split, cross\_val\_score

from sklearn.linear\_model import LogisticRegression

from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier

from sklearn.svm import SVC

from sklearn.neighbors import KNeighborsClassifier

from sklearn.naive\_bayes import GaussianNB

from sklearn.metrics import confusion\_matrix, accuracy\_score, precision\_score, recall\_score, f1\_score, make\_scorer, classification\_report

from sklearn.pipeline import Pipeline

from sklearn.metrics import roc\_curve, auc

*# Provided values for prediction*

input\_values **=** np.array([0.652174, 0.800000, 0.692308, 0.333333, 0.123054, 0.500000,

0.105015, 0.674419, 0.068333, 0.24, 0.47, 0.009804, 0.500000])

​

*# Reshape the input values to match the model's expectations*

input\_values **=** input\_values.reshape(1, **-**1)

​

*# Make predictions using the trained model*

prediction **=** model.predict(input\_values)

​

*# Display the prediction*

print("Predicted Potential Injury:", prediction[0])

Predicted Potential Injury: 0.0

**well here in the first row of the cleaned and transformed dataset(data) shows 0 which is high injury potential so here the prediction was done correctly.**

**Understanding the confusion matrix**

**True Negative (TN):**

The box correctly predicts that a person is not sick, and it turns out the person is indeed not sick.

**False Positive (FP):**

The box incorrectly predicts that a person is sick, but the person is not sick.

**False Negative (FN):**

The box incorrectly predicts that a person is not sick, but the person is actually sick.

**True Positive (TP):**

The box correctly predicts that a person is sick, and it turns out the person is indeed sick.

**[[ True Negative , False Positive]**

**[ False Negative ,True Positive]]**

**Lets find the confution matrix**

**from** sklearn.metrics **import** confusion\_matrix

​

*# Assuming you've already trained your model and made predictions*

conf\_matrix **=** confusion\_matrix(y\_test, y\_pred)

​

print("Confusion Matrix:")

print(conf\_matrix)

Confusion Matrix:

[[ 43 19]

[ 8 429]]

**Proceeding with applying other models for testing the accuracy of the prediction and possibly identifying a better model**

X\_train, X\_test, y\_train, y\_test **=** train\_test\_split(X, y, test\_size**=**0.3, random\_state**=**42)

​

*# Wrapping the classification algorithms in a Pipeline*

logistic\_regression\_pipeline **=** Pipeline([('logistic\_regression', LogisticRegression())])

decision\_tree\_pipeline **=** Pipeline([('decision\_tree', DecisionTreeClassifier())])

random\_forest\_pipeline **=** Pipeline([('random\_forest', RandomForestClassifier())])

svm\_pipeline **=** Pipeline([('svm', SVC())])

knn\_pipeline **=** Pipeline([('knn', KNeighborsClassifier())])

gradient\_boosting\_pipeline **=** Pipeline([('gradient\_boosting', GradientBoostingClassifier())])

naive\_bayes\_pipeline **=** Pipeline([('naive\_bayes', GaussianNB())])

​

*# Now I am creating a list of tuples with algorithm names and pipelines*

algorithms **=** [

('Logistic Regression', logistic\_regression\_pipeline),

('Decision Tree', decision\_tree\_pipeline),

('Random Forest', random\_forest\_pipeline),

('SVM', svm\_pipeline),

('KNN', knn\_pipeline),

('Gradient Boosting', gradient\_boosting\_pipeline),

('Naive Bayes', naive\_bayes\_pipeline)

]

​

*# This is a DataFrame to store metric reports*

metric\_report **=** pd.DataFrame(columns**=**['Algorithm', 'Accuracy', 'Precision', 'Recall', 'F1 Score'])

​

**for** algorithm\_name, algorithm\_pipeline **in** algorithms:

algorithm\_pipeline.fit(X\_train, y\_train)

y\_pred **=** algorithm\_pipeline.predict(X\_test)

accuracy **=** accuracy\_score(y\_test, y\_pred)

precision **=** precision\_score(y\_test, y\_pred)

recall **=** recall\_score(y\_test, y\_pred)

f1 **=** f1\_score(y\_test, y\_pred)

metric\_report **=** metric\_report.append({

'Algorithm': algorithm\_name,

'Accuracy': accuracy,

'Precision': precision,

'Recall': recall,

'F1 Score': f1

}, ignore\_index**=True**)

​

​

print(metric\_report)

​

Algorithm Accuracy Precision Recall F1 Score

0 Logistic Regression 0.945892 0.957589 0.981693 0.969492

1 Decision Tree 1.000000 1.000000 1.000000 1.000000

2 Random Forest 1.000000 1.000000 1.000000 1.000000

3 SVM 0.981964 0.993088 0.986270 0.989667

4 KNN 0.963928 0.979405 0.979405 0.979405

5 Gradient Boosting 1.000000 1.000000 1.000000 1.000000

6 Naive Bayes 0.943888 0.992771 0.942792 0.967136

**Cross Validation 5 folds because of computational challenges faced by my system:**

metric\_report **=** pd.DataFrame(columns**=**['Algorithm', 'Accuracy', 'Precision', 'Recall', 'F1 Score'])

​

*# Perform k-fold cross-validation (e.g., 5-fold) for each algorithm*

**for** algorithm\_name, algorithm\_pipeline **in** algorithms:

scores **=** cross\_val\_score(algorithm\_pipeline, X, y, cv**=**5, scoring**=**'accuracy')

accuracy\_mean **=** scores.mean()

precision\_scores **=** cross\_val\_score(algorithm\_pipeline, X, y, cv**=**5, scoring**=**'precision')

precision\_mean **=** precision\_scores.mean()

recall\_scores **=** cross\_val\_score(algorithm\_pipeline, X, y, cv**=**5, scoring**=**'recall')

recall\_mean **=** recall\_scores.mean()

f1\_scores **=** cross\_val\_score(algorithm\_pipeline, X, y, cv**=**5, scoring**=**'f1')

f1\_mean **=** f1\_scores.mean()

metric\_report **=** metric\_report.append({

'Algorithm': algorithm\_name,

'Accuracy': accuracy\_mean,

'Precision': precision\_mean,

'Recall': recall\_mean,

'F1 Score': f1\_mean

}, ignore\_index**=True**)

​

*# Display the metric report*

print(metric\_report)

Algorithm Accuracy Precision Recall F1 Score

0 Logistic Regression 0.931968 0.941171 0.983403 0.961798

1 Decision Tree 1.000000 1.000000 1.000000 1.000000

2 Random Forest 1.000000 1.000000 1.000000 1.000000

3 SVM 0.970496 0.980811 0.985477 0.983118

4 KNN 0.960867 0.970182 0.985477 0.977728

5 Gradient Boosting 1.000000 1.000000 1.000000 1.000000

6 Naive Bayes 0.932564 0.988284 0.933602 0.960125

logistic\_regression\_pipeline **=** Pipeline([('logistic\_regression', LogisticRegression())])

decision\_tree\_pipeline **=** Pipeline([('decision\_tree', DecisionTreeClassifier())])

random\_forest\_pipeline **=** Pipeline([('random\_forest', RandomForestClassifier())])

svm\_pipeline **=** Pipeline([('svm', SVC(probability**=True**))])

knn\_pipeline **=** Pipeline([('knn', KNeighborsClassifier())])

gradient\_boosting\_pipeline **=** Pipeline([('gradient\_boosting', GradientBoostingClassifier())])

naive\_bayes\_pipeline **=** Pipeline([('naive\_bayes', GaussianNB())])

​

*# Create a list of tuples with algorithm names and pipelines*

algorithms **=** [

('Logistic Regression', logistic\_regression\_pipeline),

('Decision Tree', decision\_tree\_pipeline),

('Random Forest', random\_forest\_pipeline),

('SVM', svm\_pipeline),

('KNN', knn\_pipeline),

('Gradient Boosting', gradient\_boosting\_pipeline),

('Naive Bayes', naive\_bayes\_pipeline)

]

​

*# Plot ROC curves for each algorithm*

plt.figure(figsize**=**(10, 8))

​

**for** algorithm\_name, algorithm\_pipeline **in** algorithms:

algorithm\_pipeline.fit(X\_train, y\_train)

y\_pred\_prob **=** algorithm\_pipeline.predict\_proba(X\_test)[:, 1]

fpr, tpr, thresholds **=** roc\_curve(y\_test, y\_pred\_prob)

roc\_auc **=** auc(fpr, tpr)

plt.plot(fpr, tpr, lw**=**2, label**=**f'{algorithm\_name} (AUC = {roc\_auc:.2f})')

​

plt.plot([0, 1], [0, 1], color**=**'navy', lw**=**2, linestyle**=**'--')

plt.xlabel('False Positive Rate (FPR)')

plt.ylabel('True Positive Rate (TPR)')

plt.title('Receiver Operating Characteristic (ROC) Curve')

plt.legend(loc**=**'lower right')

plt.show()

​

**Instrument of Survey form:**

**Survey on Predictive Analysis on MMA Fighter Injuries**

This survey is designed to evaluate the current state of predictive analysis in MMA (Mixed Martial Arts) fighter injuries. We aim to understand the challenges and opportunities in predicting and preventing injuries in MMA athletes, ultimately contributing to their well-being and safety. Your input is valuable for this research. This survey is completely anonymous and will take approximately 10 minutes to complete.

Please use the following scale to express your views regarding predictive analysis on MMA fighter injuries:  
The factors were assessed by the authors using a 6-point Likert-like rating scale in the context of MMA injury prediction:  
  
0 - Not Applicable: The model has no importance in predicting MMA injuries.

1 – Not Very Good: The model lacks essential features for predictive value for MMA injuries.

2 – Not Good: The model has some features for predicting MMA injuries but requires enhancements.

3 - Fair: The model offers a decent set of features for predicting MMA injuries and is satisfactory.

4 - Good: The model offers a comprehensive set of features for predicting MMA injuries.

5 – Very Good: The model exceeds expectations with an extensive set of features for predicting MMA injuries.

What is your age\*

Your answer

What is your gender\*

* Male
* Female
* Other:

How many severe injuries have you experienced in your MMA career thus far?\*

Your answer

What weight class do you typically compete in?\*

* Featherweight
* Lightweight
* Welterweight
* Middleweight
* Light Heavyweight
* Heavyweight
* Other:

What is your primary fighting stance in MMA?\*

* Orthodox (Right-handed)
* Southpaw (Left-handed)
* Switch Stance (Switching between orthodox and southpaw)
* Open Stance
* Other:

What level of experience do you have as an MMA fighter?\*

* Amateur
* Pro
* Novice
* Intermediate
* Expert

How many hours per week do you typically spend on MMA training\*

Your answer

How often do you participate in sparring sessions?\*

* Rarely
* Occasionally
* Weekly
* Several times a week
* Daily

What do you consider the most common type of injury in MMA?\*

* Concussions
* Joint injuries (e.g., knee, elbow)
* Cuts and abrasions
* Bruises and contusions
* Other:

Are you satisfied with the safety measures and medical support in the MMA organization you compete in?\*

* 0 - Not Applicable
* 1 – Not Very Satisfied
* 2 – Not Satisfied
* 3 – Fair
* 4 – Good Satisfaction
* 5 – Very Good Satisfaction

How relevant is your fighting stance to your injury experiences in combat sports?\*

* 0 - Not Applicable
* 1 – Not Very Good Relevance
* 2 – Not Good Relevance
* 3 – Fair
* 4 – Good Relevance
* 5 – Very Good Relevance

Do you follow a specific dietary regimen for training and recovery purposes?\*

* Yes, these factors do play an important role in recovery and training
* To some extent these factors do play an important role in recovery and training
* No, these factors do play an important role in recovery and training

How confident are you in your ability to recognize the signs of overtraining and prevent it?\*

* 0 - Not Applicable
* 1 – Not Very Confident
* 2 – Not Confident
* 3 – Fair
* 4 – Good Confidence
* 5 – Very Good Confidence

How relevant do you believe your fighting stance is to the risk of injuries in combat sports?\*

* 0 - Not Applicable
* 1 – Not Very Good Relevance
* 2 – Not Good Relevance
* 3 – Fair
* 4 – Good Relevance
* 5 – Very Good Relevance

What are your thoughts on incorporating machine learning for injury prediction in your training?\*

* 0 - Not Applicable
* 1 – Not Very Good Relevance
* 2 – Not Good Relevance
* 3 – Fair
* 4 – Good Relevance
* 5 – Very Good Relevance

How do you think technology, such as machine learning, will impact your training and injury prevention in MMA?\*

* 0 - Not Applicable
* 1 – Not Very Good Relevance
* 2 – Not Good Relevance
* 3 – Fair
* 4 – Good Relevance
* 5 – Very Good Relevance

How crucial is early injury detection and prevention in your MMA career?\*

* 0 - Not Relevant
* 1 - Not Very Crucial
* 2 - Not Crucial
* 3 - Fair
* 4 - Crucial
* 5 - Very Crucial

What is your level of concern about using machine learning for early injury prevention in MMA?\*

* 0 – Not Relevant
* 1 - Very minimal concern
* 2 - Slight concern
* 3 - Fair
* 4 - Good support
* 5 - Very confident and strongly supportive of using machine learning for early injury prevention in MMA

How do you think age, weight, and fighting style might affect injury risks?\*

* 0 - Not Applicable
* 1 – Not Very Good Relevance
* 2 – Not Good Relevance
* 3 – Fair
* 4 – Good Relevance
* 5 – Very Good Relevance

How open are you to the idea of contributing your data for research aimed at personalized injury prevention in MMA?\*

* 0 - Not Applicable
* 1 – Not Very Open
* 2 – Not Open
* 3 - Fair
* 4 - Open
* 5 – Very Open