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Behavioral System to Detect Injury and Rehabilitation Process in Karate Using Hybrid Model

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Abstract

Sports injuries are becoming increasingly widespread, and professional player injuries are having a negative impact on the field of sports. Preventing sports injuries is becoming more popular. Numerous machine learning (ML) techniques have been used in different sports injury fields since the birth of ML. In order to deal with the issue of karate injury treatment, rehabilitation, and prevention, this paper presents a new behavioral system to identify injuries and the rehabilitation process in karate utilizing hybrid models that mix unsupervised learning and supervised learning. In our scenario, we picked Autoencoder for unsupervised learning and CNN and DNN models for supervised learning. The experimental investigation shows that the suggested model is capable of yielding accurate outcomes. In fact, our model's accuracy for DNN and CNN is 99.67% and 99.66%, respectively.

Keywords: machine learning, injury sports, DNN, CNN, deep learning, artificial neural network, unsupervised learning, supervised learning, hybrid model

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1. Introduction

Karate is said to have originated on Okinawa from native Okinawan fighting techniques, as well as Chinese and Japanese martial arts. It was introduced to Japan in the early 20th century, and by the middle of the century, its popularity had grown. As the first global karate governing body, the World Karate Federation (WKF) was established in 1970 and currently has 191 member nations. Karate is getting more and more popular worldwide, and in 2020 it will make its Olympic debut in Tokyo. Now, kata and kumite events with individual and team elements can be seen in karate tournaments. Kumite is free combat with an opponent using the same techniques, whereas kata is the application of prepared techniques without any direct confrontation.

A complicated, hard, and risky sport is karate. These days, as athletes try to be as effective as possible during practice and competition, their injuries often get worse. Numerous indicators point to the fact that sports injuries are on the rise and are a major concern for sportsmen. Technical errors, insufficient intensity, prolonged time, excessive repetitions, or abrupt movements are the main causes of athlete self-injury. Additionally, the likelihood of an athlete suffering from a sports injury increases with the duration of their physical activity and the severity of the ailment. The most frequent wounds suffered in martial arts are cuts, bruises, sprains, and strains. A bone may also fracture. Injury to the knee, ankle, shoulder, and elbow is among the most frequent ones. When practicing martial arts that entail hitting, the hands are especially vulnerable to harm. The lack of ability to "see", evaluate, and compare harm at the tissue level, according to Flint [1], is the root cause of the variety of injury classifications.

Understanding the traits, causes, treatment options, and prevention of karate injuries is essential to approaching the issue of karate injury prevention, treatment, and rehabilitation. The fundamental properties of karate, as well as its distinct physical features, must also be understood by individuals, as must any potential connections between these elements and injuries. A detailed examination of the physical attributes of karate, the project's attributes, and the characteristics of injuries is followed by the search for an all-encompassing set of risk assessment procedures.

Studying the factors that assist athletes in reducing IR is crucial. Injuries cannot be completely eliminated in karate since it has not yet been established that impacts that exceed the mechanical resistance of tissues are the primary cause of major injuries. Karate assaults specifically target vulnerable parts of the opponent's body, so any modifications to the rules of combat set forth by sports federations can only partially lessen the risk of injury. This article, which uses CNN and DNN models from deep learning, suggests a novel behavioral approach to detect injuries and the recovery process in karate in order to allay these worries.

2. Literature review

The scientific study of statistics and mathematics that allows computers to learn from experience and make better decisions is known as machine learning. A wide range of scientific, medical, and financial domains have benefited from the application of machine learning, including image identification, cancer detection, stock market forecasting, and customer churn prediction [1, 2]. In many domains, including athletics, machine learning is still in its infancy [2, 3]. Sports injuries are attracting the attention of more sports medicine researchers, despite the fact that many of them lack expertise with psychological evaluation methods. For instance, Everhart *et al.* used 34 psychological component evaluation measures in 152 sports injury treatment outcome studies that included psychological evaluations prior to and following therapy [4].

Machine learning methods were used in 2023 by Dandrieux *et al.* [5] to estimate the risk of injury in 284 male football players who were members of 16 professional or semi-professional football clubs from three different nations. Three models adaBoost, random forests, and logistic regression were contrasted using a dummy classifier. The findings demonstrated that using these models, it is possible to forecast the likelihood of injury to some degree. Tondut and others [6] in 2023, they make an effort to calculate the risk of injury for 110 athletes who compete in sports that need repeated sprints (bobsleigh, rugby at 7, athletics, and athletics). A decision tree model was trained and refined to predict the probability of an injury based on the variables that were measured. Both the Sports Medicine Diagnostic Coding System and the Sports Injury Disease Classification System were updated in later editions by Orchard *et al.* to incorporate the new consensus categories [7].

In addition to providing a number code for the effect of injuries on motor function, Bj *et al.* released the Orchard Sports Injury Classification System, a Spanish translation of the Sports Injury Classification System's 12th edition [8]. Osteoarthritis in the knee is associated with trauma to the knee. The Inaa *et al.* study set out to determine the likelihood of KR surgery and to pinpoint medical costs for the 10 to 15 years after a sports injury [9]. Even while previous studies have significantly improved sports injury prevention, there are still glaring inadequacies in the effectiveness of injury prevention. There has been a lot of interest in applying machine learning to sports injuries, and various academics have conducted research in this area. Desmond M emphasized the efforts made by the US Olympic Ski Team to improve training methods and results in competition by utilizing machine learning (ML) and remote sensor telemetry. In the context of motion dynamics, this section examines the potential applications of machine learning [10].

To encourage children's interest in machine learning, Zimmermann-Niefield *et al.* offered a number of simple and effective methods for them to use sensors sensibly when exercising [11]. The problem brought up by Pappalardo *et al.* has attracted a lot of attention from companies and the scientific community since machine learning algorithms can gather massive amounts of data that can be utilized to avoid sports injuries using electronic data. assessing football players' performance [12].

Numerous machine learning techniques have been used to examine the effects of sports injuries, and Mittal *et al.* developed a machine learning architecture to monitor these effects in real time [13]. Even though using machine learning to avoid sports injuries improves preventative effectiveness, the field is now too complex for it to be appropriate. Using a hybrid model as an innovation, this research suggests a novel behavioral technique to identify injury and the healing process in karate.

3. Fundamentals

Two of the most important aspects of the study described in this paper are the concepts of injury detection and the machine learning (ML) techniques utilized to evaluate the dataset; these topics are covered in length in this section.

3.1. Types of karate injuries

Due to the comparable muscle groups used in martial arts, the injuries that athletes may sustain from them generally share similar traits. Chops, deflection of blows, and throws can all cause injuries to an athlete's hands, wrists, forearms, and/or elbows. Fractures and dislocations are still the two injury kinds that karate practitioners experience the most frequently. Figure 1 displays the most typical karate injuries.

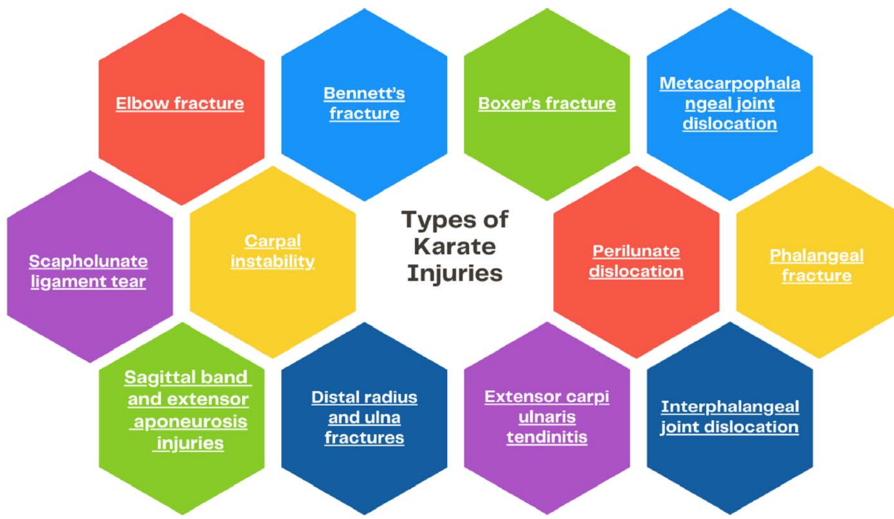

Figure 1. Types of karate injuries.

3.2. Features reduction technique

An autoencoder is a technique for decreasing the size of a dataset's feature set while maintaining overall classification performance. An encoder and a decoder are symmetrical components of autoencoder neural networks. The decoder reconstructs the input data using the qualities, also known as latent representations, extracted from the raw data by the encoder. Figure 2 shows the Autoencoder's organizational structure.

3.3. Used models (DNN, CNN)

We have employed the two models discussed in this part to assess our strategy.

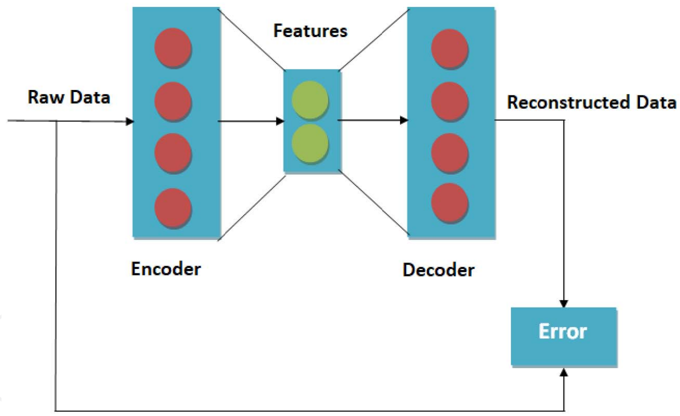

Figure 2. An autoencoder structure.

• Deep Neural Network Model (DNN)

The layers of a DNN model are input, hidden, and output. Each layer has several nodes that are hierarchically related to all nodes in the following layer. In most cases, the input and output layers are single layers, but the concealed layer may have two or more levels. After being processed in the hidden layers, data attributes are provided into the input layer, and estimations are obtained from the output layer. Each hidden-layer node contains an activation function that takes as input the weighted sum of nodes and converts it into useful values. The weighted sum of nodes is utilized to generate expected values with this activation function. If the weighted sum of the nodes is larger than or equal to zero, the rectified linear unit (ReLU), the most commonly used activation function in regression analysis, generates a value equal to the input; otherwise, it generates a value of zero. Figure 3 depicts the structure of the DNN.

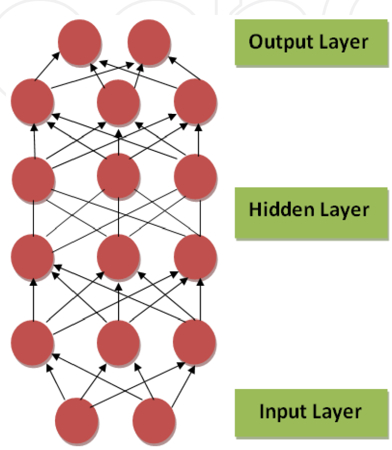

Figure 3. The structure of the DNN.

- Convolutional Neural Network (CNN)

One kind of neural network that can automatically recognize and classify the unique characteristics of the neural network is a CNN. This deep learning technique uses a feed-forward network, which suggests that it takes an input and applies learnable weights and biases to its features.

Every neuron in this artificial neural network has a non-linear activation function, which produces the final output. Together, a few neighboring connected neurons form a kernel, also called a weight matrix. A "convolution layer" (CONV) is made up of many kernels, each of which produces an output. The CONV layer carries out convolution processes while scanning an input. It achieves this by making use of its numerous hyper-parameters, which are pre-set before the learning process starts and can have an impact on how well a model trains. These hyper-parameters include the filter size, which indicates the size of a filter that is applied in the process, and the stride, which specifies the number of pixels by which the window moves after each operation. A feature map, sometimes referred to as an activation map, is the resultant output.

The next stage in the processing chain is the pooling layer (POOL), a down-sampling method that collects the maximum and average values of a certain region while implementing some spatial invariance. The network gathers these values and proceeds to the fully connected layer (FC), where every input is coupled to every neuron. A common CNN input is an image vector containing a set of enclosed features. The image vector generates a probabilistic approximation that can identify the target image after it has gone through each of these levels. One major benefit of this approach is that it requires significantly less preprocessing on a conventional CNN than other classification algorithms. Figure 4 shows the organizational chart for CNN.

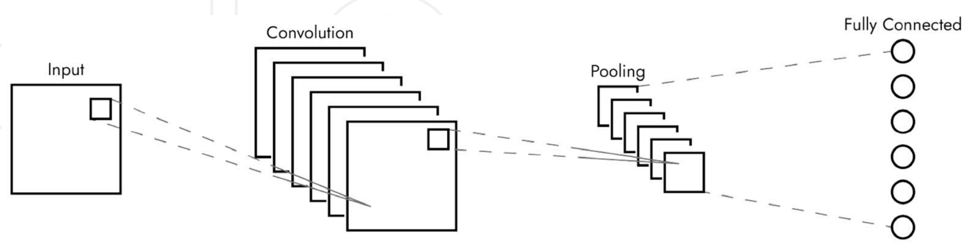

Figure 4. The structure of a CNN.

3.4. Machine learning methods

Machine learning is an intriguing branch of artificial intelligence that preserves knowledge by preparing data based on known facts. The main focus of machine learning is expectations. As seen in Figure 5, there are three types of machine learning techniques: supervised learning, unsupervised learning, and reinforcement learning. We can cite Mehta *et al.* [14] and Calitoiu *et al.* [15] as two of the many works from today that have employed these techniques.

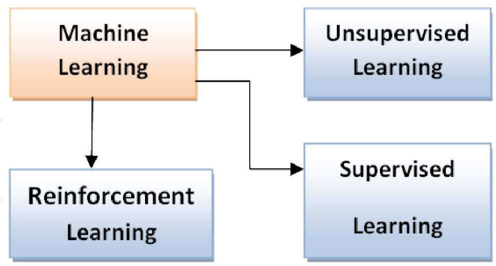

Figure 5. Machine learning methods.

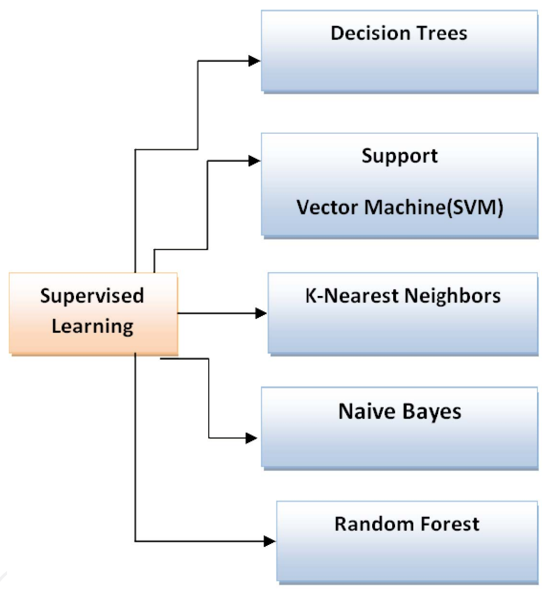

Figure 6. Supervised machine learning classification.

• Supervised Machine Learning

Another name for supervised learning is order. Cases are marked during the supervised learning data preparation phase. There are a few supervised learning methods at your disposal. Quadratic classifiers are the most well-known supervised learning algorithms (Figure 6) . Other supervised learning methods include Bayesian Statistics, Gaussian Process Regression, Lazy Learning Support Vector Machine, Hidden Markov Model, Bayesian Networks, Decision Trees, K-nearest neighbor Boosting, Linear Classifiers, and Ensemble Classifiers.

• Unsupervised Machine Learning

Unlabeled examples can be found in unsupervised learning data. One of the main learning pathways in this system is grouping. Cluster examination (K-implies grouping, Fuzzy bunching), Hierarchical grouping, Self-sorting out guide, A priori calculation, Eclat calculation, and Outlier detection (Local exception factor) are examples of regular unsupervised machine learning. Figure 7 depicts unsupervised machine learning classification.

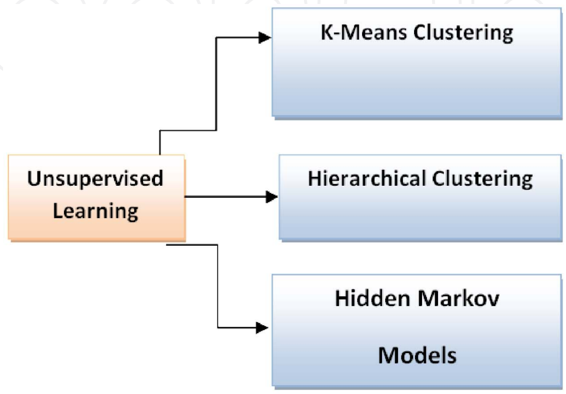

Figure 7. Unsupervised machine learning classification.

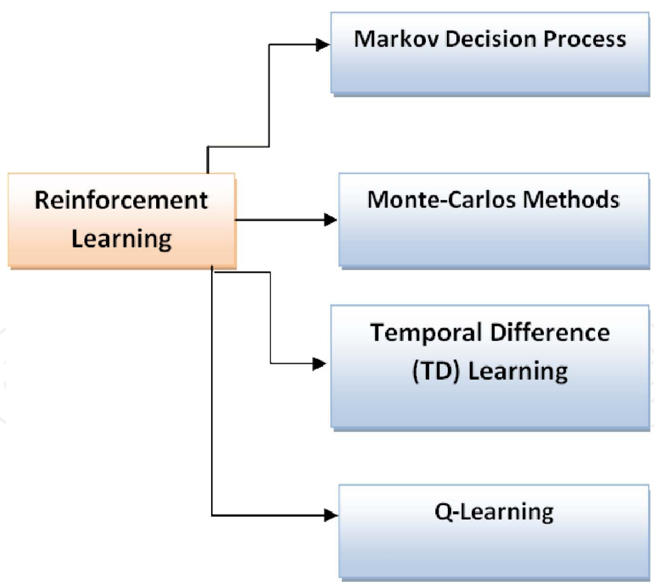

Figure 8. Reinforcement Learning classification.

• Reinforcement Learning

PCs engage with a domain in reinforcement learning in order to accomplish a particular objective. A client (such a domain master) might be asked to identify a case from a big collection of unlabeled examples using a reinforcement strategy (Figure 8) .

4. Our proposed approach

This section introduces our Behavior Karate AI methodology. The scenario of our approach is shown in the Figure 9.

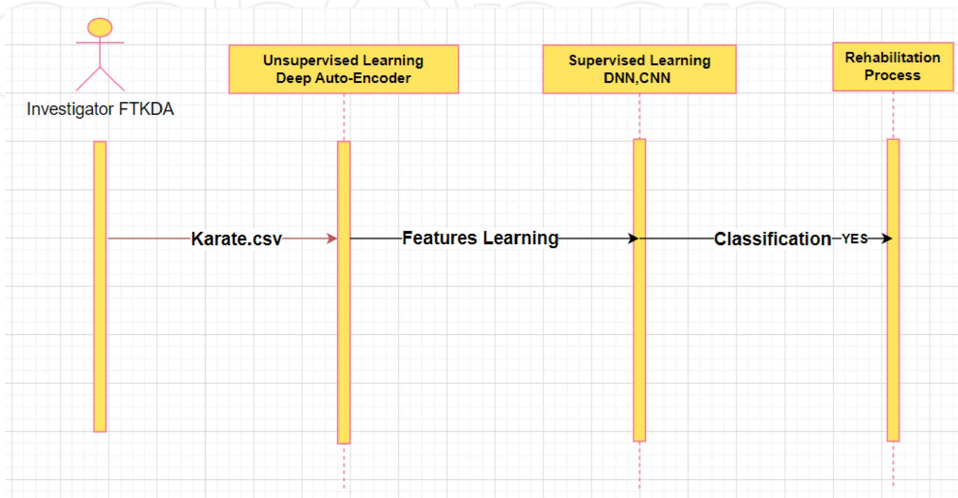

Figure 9. The scenario of our approach.

Four primary phases comprise the suggested approach, as seen in Figure 10: data collection, supervised classification, unsupervised feature learning, and the rehabilitation process. First, inconsistencies (Infinity, NaN, and null values) are eliminated. The second uses a deep autoencoder to carry out unsupervised learning. To create a new representation of the characteristics and minimize the dimensionality of the unlabeled data, the auto-encoder is utilized. Based on the results of the first phase, a deep neural network (DNN) or a convolutional neural network (CNN) is then used in the third step to carry out supervised learning classification.

The process of rehabilitation is presented in the fourth step. The ensuing subsections include more information.

Phase 1: Procedure for gathering data. The primary goal of this phase is data preparation and gathering. In our instance, information was gathered through a test administered by the Tunisian Karate Federation. All of the data that we gathered is contained in a file called karate.csv.

Phase 2: unsupervised learning. When numerous features are available, the complexity of the generated model may grow as a result of noise and redundancy,

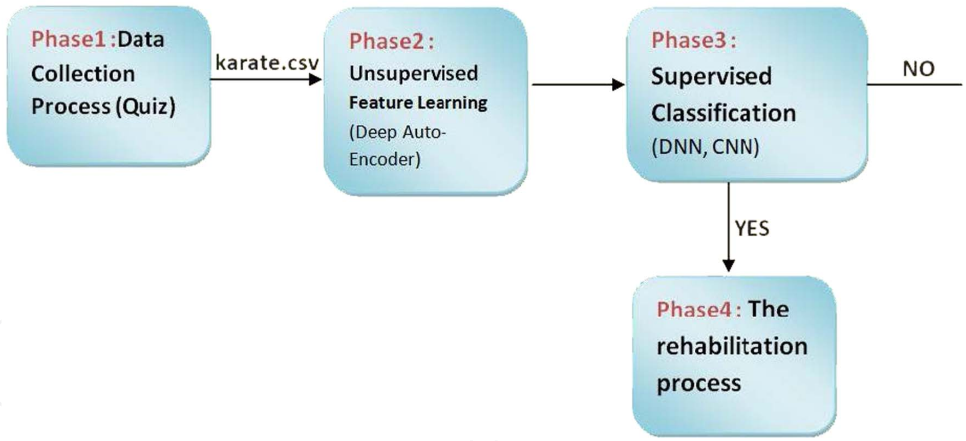

Figure 10. Our suggested methodology Conduct Karate-AI.

which may impair learner performance. By shrinking the size, these issues can be resolved. The adjustments required to extract the most significant features from unlabeled data inputs are made using a feature extraction technique. Following the production of low-dimensional data, the classifier will be categorized to improve its worldwide efficiency. As an unsupervised neural network approach, we employed an autoencoder at this phase. Its primary goal is to replicate the original input as a reduced, equivalently rebuilt output.

Phase 3: Supervised classification. The newly derived feature space and the class vector from the original dataset will be joined in this stage. Consequently, we are left with a condensed and labeled training set that our preferred classifier can use as input data. Numerous supervised learning methods exist, including decision trees, convolutional neural networks (CNNs), deep neural networks (DNNs), random forests, and neural network classification rules.

We have chosen Deep Neural Network (DNN) and Convolutional Neural Network (CNN) as our two supervised classifiers for this challenge. In this instance, we decided to use the online Google Colab workspace. We used two models to assess the CNN and DNN datasets and the autoencoder for the feature reduction method to evaluate our approach.

Phase 4: The rehabilitation process. In this stage, if there are injuries, the doctor proposes a strategy for rehabilitation. Injury severity was assessed based on days without physical activity. We have established four levels of severity:

- Level 1: No suspension of activity.
- Level 2: suspension of less than 8 days;
- Level 3: 8 to 30 days of unavailability.

- Level 4: 30 days or more of interruption or requiring hospitalization, cast or surgical care.

5. Material and method

5.1. Study design and overall procedure

Based on exploratory research, a cross-sectional study was conducted in which athletes sanctioned by the Tunisian Karate Federation (FTKDA, ftkarate.com) were asked about their perceptions, communication preferences and expectations regarding the relevance injury prevention. The study was reviewed and approved by the scientific committee Faculty of Economics and Management of Sfax (FSEG).

5.2. Survey and data collection

We worked on our quiz at the Tunisian Federation of Karate, which is an organization aimed at promoting the discipline of karate and the sports associated with it, in Tunisia. One hundred and twenty-five practitioners at the Tunisian Federation of Karate approved were interviewed over the period from May 2022 to January 2023. The quiz were first obtained in the form of face-to-face interviews, after distributing paper quiz that the club's karate members could read. For missing subjects and incomplete forms, contact was made by telephone. It is the same person who collected all the data. The investigation scenario is shown in the Figure 11.

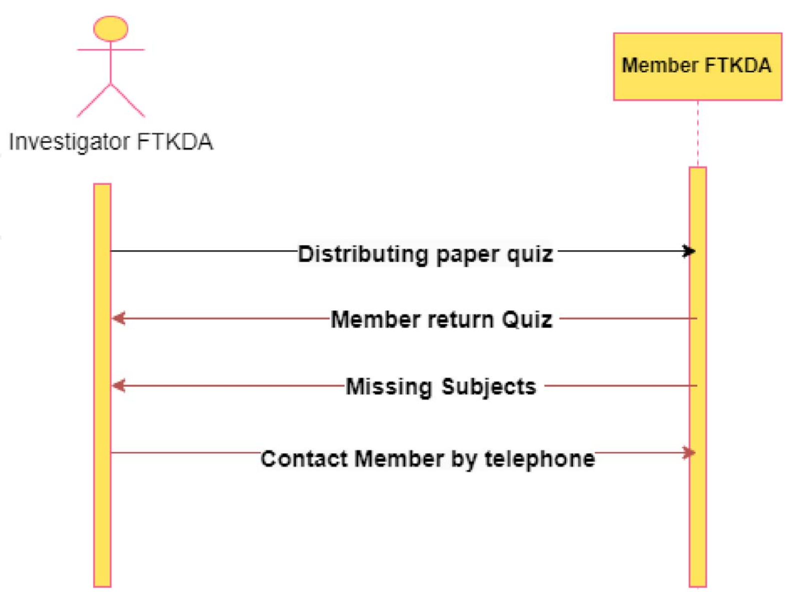

Figure 11. The investigation scenario.

The quiz makes it possible to list:

- Personal data (name, club, age, grade, number of years of practice, number of hours of training per week during the study period);
- Injury (type, location, mechanism, movement during) occurring during.

The study population included 125 athletes (54 women, 71 men). The average age of the study population ranged from 18 to 22 years and older. Table 1 contains detailed data and information on the age of the participants. Figure 10 includes the sex of the participants. The response rate to the quiz is 89.29%. The study population is divided into eight categories:

Table 1. Age of participants.

Age	Number of participants	Percentage (%)
18–20	67	53.6
20–22	43	34.4
22+	15	12

- Forty (32%) were white or yellow belts (beginners).
- 60 (48%) were orange, green or blue zones (medium price level);
- And 25 (20%) brown or black belts (with experience).

Injury severity was assessed based on days without physical activity. We have established four levels of severity:

- Level 1: No suspension of activity.
- Level 2: suspension of less than 8 days;
- Level 3: 8 to 30 days of unavailability.
- Level 4: 30 days or more of interruption or requiring hospitalization, cast or surgical care.

6. Evaluation and discussion

Accuracy, Precision, Recall, F1-score, and Area under the receiver operating characteristics (ROC) curve are used to compare and assess the suggested approach. We employed the macro and micro averages of Recall, Precision, and F1-Score in this work. Score for multi-class classification. All of the metrics listed above can be produced with the use of the confusion matrix (CM). Table 2 demonstrates CM is designed for binary classes, but it can be extended to many classes.

Table 2. Illustration of confusion matrix.

		Class$_{pos}$	**Class$_{neg}$**
Actual	Class$_{pos}$	True Positive (TP)	False Positive (FP)
	Class$_{neg}$	False Negative (FN)	True Negative (TN)

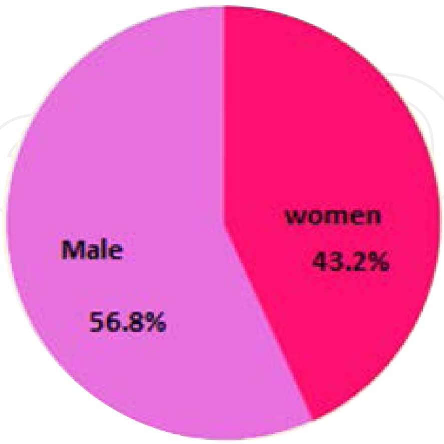

Figure 12. Comparison with other works available in the literature.

In Table 2, True positive (TP) refers to the amount of class$_{pos}$ data predicted that actually belongs to class$_{pos}$, True negative (TN) refers to the amount of classneg data predicted that actually belongs to class$_{neg}$, False positive (FP) refers to data predicted as class$_{neg}$ but actually belongs to class$_{pos}$, and False negative (TN) refers to data predicted as class$_{neg}$ but actually belongs to class$_{pos}$. The evaluation metrics are calculated using the terms listed above.

Accuracy: It is the proportion of cases that are correctly classified to all occurrences. It is also known as detection accuracy, and it is only a valuable performance metric in balanced datasets.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

Precision (P): To all the samples predicted as Attacks, it is the ratio of accurately predicted Attacks to all the samples.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

Recall (R): It represents the proportion of samples that are indeed attacks to samples that were accurately identified as attacks. It also goes by the name "Detection Rate."

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

F-measure (F): Its definition is the Precision and Recall harmonic mean. Stated differently, it is a statistical method for assessing a system's correctness by taking into account the system's recall and precision.

$$\text{F1} - \text{Measure} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

To assess the effectiveness of our suggested strategy, we prepared a database from the quiz carried out within the Tunisian Karate Federation. We created a csv file "karate.csv", which contains all the information about the athletes: name, age, date of birth, number of injuries,... This file was an input into our model. In our instance, we decided to work on a Google Research product called Google Colab. Colab respects data privacy rules by enabling anyone to write and execute any Python code through a browser. It is a very good setting for teaching, learning from data, and machine learning. Technically speaking, Colab is a hosted Jupyter notebook service that offers free access to computer resources, including GPUs, and doesn't require any configuration. For supervised learning, we used CNN and DNN models, and for unsupervised learning, we used Autoencoder. We've run multiple tests on our model. The optimal experimental outcomes of our CNN and DNN models are displayed in Table 3.

Table 3. Overall performance (karate dataset).

Model	Accuracy	F1 score	Recall	Precision
Deep Neural Network (DNN)	0.9967	0.9998	0.9983	0.9979
Convolutional Neural Network (CNN)	0.9966	0.9982	0.9978	0.9986

An attempt should be made to better understand the relationship between training and competition load and injuries in order to quantify tiredness and recovery, better comprehend adaptability to training programs, and lower the risk of illness and injury. Several data points have been combined in karate for analysis and damage prediction. But it wasn't until lately that the right statistical methods were applied to examine the accessible data set.

The intricacies of the relationship between player load and injury are now more understood because to machine learning's advancements in autonomous and interactive data analysis. Our methodology has already been put to the test in the intrusion detection domain, and we have presented the findings at two international conferences.:

- "Behavioral System for the Detection of Modern and Distributed Intrusions based on Artificial Intelligence techniques: Behavior IDS-AI" in the 6th International Joint Conference on Advances in Computational Intelligence IJCACI 2022 [16].

- “Behavior Intrusion Detection System Using SVM And CNN” in the Congress on Smart Computing Technologies (CSCT 2022) [17]. In this work, we chose to apply our model in the field of karate to detect injuries, and we noticed that our model is efficient and gave us good results.

We compare our approach here with several works that are worked on maching learning: Vallance *et al.* [18], Naglah *et al.* [19], Kamakis *et al.* [20], Jauhiainen *et al.* [21], Henriquez *et al.* [22], Lovdal *et al.* [23], Van Eetvelde *et al.* [24], Taborri *et al.* [25], Majumdar *et al.* [26]. Table 4 compares our best findings with other writers' findings regarding sports injuries.

Table 4. Comparison with other works available in the literature.

Type	**ACC (%)**
OUR MODEL (DNN)	99.67
OUR MODEL (CNN)	99.66
Vallance *et al.* [18]	95.00
Naglah *et al.* [19]	99.50
Kamakis *et al.* [20]	66.04
Jauhiainen *et al.* (Logistic Regression) [21]	65.00
Jauhiainen *et al.* (Random Forest) [21]	63.00
Henriquez *et al.* [22]	79.00
Lovdal *et al.* [23]	78.00
Van Eetvelde *et al.* [24]	52.00–87.00
Taborri *et al.* [25]	96.00
Majumdar *et al.* [26]	83.50–97.07

Figure 13 presents an accuracy comparison between the proposed Behavior Karate-AI model and other benchmark models, demonstrating that Behavior Karate-AI has a greater accuracy than the other models. The suggested Behavior karate-AI model beats its comparison peers in terms of accuracy, reaching 99.67% and 99.66% for DNN and CNN, respectively. Table 3 compares the proposed model and existing literature models in terms of accuracy. In certain instances, the findings are aggregated and do not reveal information about the injuries found, and some of the models under comparison do not employ crossvalidation. The overall result demonstrate the value of using Behavior karate-AI to detect injuries in the data set, even though more research is need to compare our findings with those of the literature. By using these techniques, one can maintain the results with those of other comparable works while somewhat reducing the performance gained.

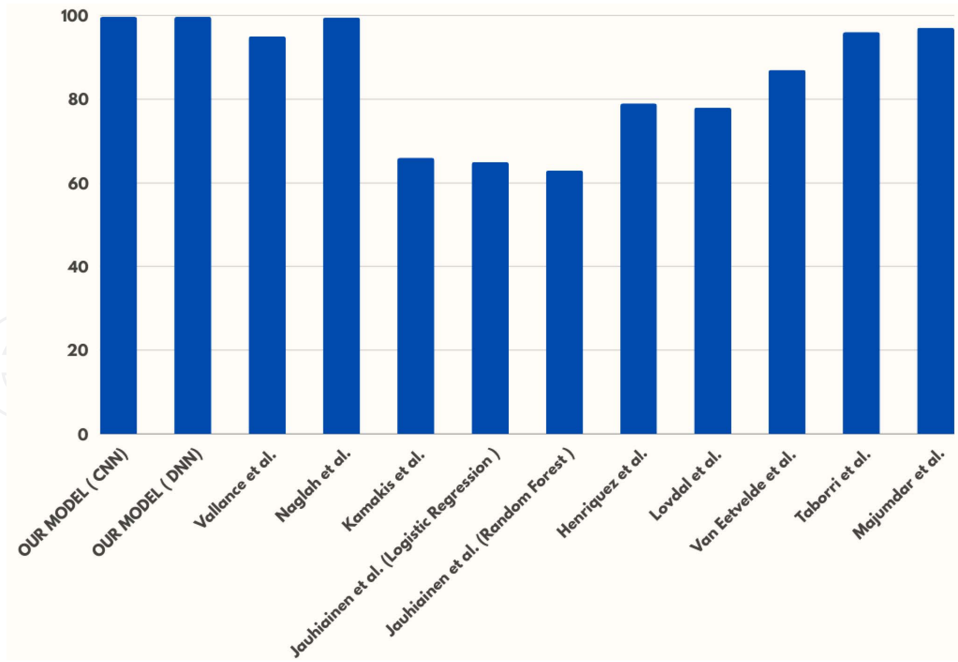

Figure 13. Comparison with other works available in the literature.

7. Conclusions

By using predictive models such as CNN and DNN, existing incorrect predictions due to excessive complexity are challenged and interactions between variables are minimized. In karate, such algorithms can be used to detect damage. This helps to identify factors of sport-related karate injuries in the general population. Increased awareness, the existence of legislation mandating the use of protective gear in high-risk sports, and encouraging players to wear protective gear regularly can all help reduce the number of karate injuries. Athletes should be educated about the dangers of karate injuries and their consequences.

This article proposes a new behavioral system for detecting injuries and the rehabilitation process in karate using a hybrid model. We evaluated our strategy using two models to analyze the CNN and DNN datasets, as well as the autoencoder for the feature reduction method. Empirical research demonstrates that the suggested model can produce reliable outcomes. Indeed, our model's accuracy for DNN is 99.67%, while for CNN it is 99.66%. Future research will include more potent tactics to raise the detection rate and precision of our approach.

Conflict of interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

Competing interests

The authors declare that they have no competing interests.

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Author contributions

The authors contributed equally to this work.

Research data policy and data availability statements

Data sharing apply to this article because a dataset was generated and analyzed during the current study.

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