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Original Research Paper

Optimizing Injury Detection with Autoencoder-Based Classifiers and Feature Selection

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Abstract: Many machine learning applications, such as injury detection systems, have made extensive use of autoencoders. For instance, it was suggested to use improved representative features in a deep autoencoder-based injury detection system to increase detection accuracy. Similarly, a feature selection based on the agricultural fertility algorithm was used to enhance injury detection systems, demonstrating the potential of feature selection techniques in improving detection performance. This study investigates the combination of autoencoder-based classifiers for injury classification and training. This method is used on the most significant feature chosen using the chi-square test (for binary values) and Pearson correlation (for continuous values). For the experiment, we have used the dataset. The study included 250 athletes, 150 of whom were women and 100 of whom were men. The average age of the study participants ranged from 18 to 22 years old. The quiz's response rate is 90.30%. The results of the trial show that the Injury Detection System outperforms previous studies and other classifier techniques, achieving a high classification accuracy of 92.27%.

Keywords: Autoencoder, Classification, Feature Selection, Injury Detection, Machine Learning.

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1. Introduction

In recent years, there has been a growing interest in the application of autoencoders for injury detection in various fields. Autoencoders are a type of artificial neural network that can learn efficient representations of input data by training the network to reconstruct the input at the output layer. One of the key areas where autoencoders have been applied for injury detection is in the field of structural health monitoring (SHM) [1].

The study by Mechanics-informed autoencoder enables automated detection and localization of damage in structures [2] introduces the Mechanics-Informed Damage Assessment of Structures (MIDAS) framework, which utilizes autoencoders for automated damage detection and localization in near-real-time. This framework gives structural engineers and maintenance staff a useful tool by utilizing autoencoders' abilities to evaluate structural data and spot any deterioration.

A correlation-based approach to damage identification using Variational Autoencoder neural networks is presented in another article, Structural Damage Detection Based on the Correlation of Variational Autoencoder neural networks [3]. This method shows how autoencoders can use correlations in the data to precisely detect and identify structural deterioration. Researchers can create more dependable and effective techniques for detecting structural degradation by utilizing autoencoders. The diagnosis of sports injuries has also made use of autoencoders.

In addition, a study on a stacked autoencoder-based aid system for severity degree [4] focuses on knee ligament rupture, one of the most common injuries that frequently require complex diagnostic methods for severity assessment. This study explores the use of autoencoders in deep learning to efficiently retrieve MRI data from databases for sports injury diagnosis. By integrating autoencoders into the diagnostic process, healthcare professionals can streamline the retrieval and analysis of medical imaging data, resulting in more accurate and timely diagnoses of sports-related injuries. This approach seeks to give medical practitioners a more effective and precise tool for determining the degree of knee injuries by utilizing autoencoders. Autoencoders have been used for injury identification in a variety of fields, including sports and structural injuries.

The use of autoencoders for fall detection, especially among the elderly population, is examined in the research named Novel Approach for Fall Detection Using Thermal Imaging and a Stacking Ensemble of Autoencoder and 3D-CNN Models [5]. The researchers show how autoencoders may be used to create novel fall detection methods that use thermal imaging technology, which is essential for reducing injuries and mortality from falls. With the help of autoencoders, researchers and medical professionals can create more effective, precise, and timely methods for identifying and evaluating injuries, which will ultimately improve patient outcomes and safety.

Overall, the reviewed studies demonstrate the wide range of applications of autoencoders for injury detection in different fields, such as fall detection, sports injury diagnosis, and structural health monitoring. This study investigates the combination of autoencoder-based classifiers for injury classification and training.This method is used on the most significant feature that was chosen using the chi-square test (for binary values) and Pearson correlation (for continuous values). The results of the trial show that the Injury Detection System outperforms previous studies and other classifier techniques, achieving a high classification accuracy of 92.27%. For experiment we have used the dataset [6]. The study's findings have important practical applications, especially in the fields of sports science and injury prevention. This method can assist athletes, coaches, and medical professionals in tracking physical activity and identifying early indicators of damage by utilizing statistical feature selection and autoencoder-based classifiers.

2. Literature Review

Detecting anomalies is a crucial problem in many domains, such as transportation systems, cybersecurity, and industrial monitoring. Conventional approaches frequently have trouble with feature collapse, detecting anomalous hidden features, and managing massive volumes of temporal data. Researchers have used deep learning methods, especially autoencoders, to create more potent anomaly detection models in order to overcome these obstacles. The incorporation of memory modules into autoencoder models is one method for enhancing anomaly detection. The use of autoencoders for injury detection in a variety of disciplines has gained popularity in recent years. By training the network to reconstruct the input at the output layer, autoencoders a kind of artificial neural network are able to develop effective representations of input data. Based on the relevant documents that have been presented, the purpose of this literature review is to investigate the usage of autoencoders for injury detection. One of the key applications of autoencoders in injury detection is in the field of structural health monitoring (SHM).

The study by the authors in [3] introduces the Mechanics-Informed Damage Assessment of Structures (MIDAS) framework, which utilizes an autoencoder for automated damage detection and localization in near-real-time. By incorporating mechanical information into the autoencoder model, the framework can effectively identify structural damage and its location. Another study, as presented in [4], focuses on structural damage detection using a correlation-based method with Variational Autoencoder neural networks. This approach leverages the capabilities of autoencoders to learn the underlying correlations in the data and identify damage in structures based on variations in the input signals.

Autoencoder-based photoplethysmography (PPG) signal dependability has been used in the construction industry to reduce occupational injuries [7]. Convolutional autoencoders have also been used to enhance yarn quality through wavelength spectrogram analysis [8]. The combination of denoising autoencoders with bidirectional LSTM neural networks for automatic auditory novelty identification has also improved biomechanical machine learning with minimal data [9]. Autoencoders have shown themselves to be useful instruments in the field of anomaly identification. Autoencoders based on convolutional neural networks (CNNs) have been used to improve anomaly identification in high-dimensional datasets, as those pertaining to injuries [10]. Additionally, the potential of autoencoders in environmental monitoring has been demonstrated by the early detection of dark-affected plant mechanical responses by the use of an Autoencoder (AAE) structure to augment samples [11]. Predicting the risk of sports injuries is another area where autoencoders have showed promise. To enhance the identification of non-contact injury risk in top Australian athletes, a novel method based on time series data and autoencoders has been developed [12].

To sum up, autoencoders have demonstrated great promise in injury detection across a variety of fields, such as fall detection, sports injury diagnosis, and structural health monitoring. By utilizing autoencoders' capacity to learn effective representations of input data, researchers have been able to create automated systems for accurately and efficiently detecting and localizing injuries. More research in this area is likely to progress injury detection technologies and improve outcomes for people who are at risk of injury. This paper explores the use of autoencoder-based classifiers in conjunction with training for injury classification.Using the chi-square test (for binary values) and Pearson correlation (for continuous values), the most important feature is selected and subjected to this procedure. The trial's findings demonstrate that the Injury Detection System performs better than prior research and alternative classifier approaches, with a high classification accuracy of 92.27%. The dataset [1] was utilized for the experiment.

3. Methodology

The proposed methodology, which comprises four essential steps data preparation, feature selection, classification, and model evaluation is then thoroughly described. To improve clarity, Figure 1 provides an illustrated picture of the complete workflow by visualizing these steps.

3.1. Description of Dataset

This cross-sectional study, which was based on exploratory research, surveyed athletes who were authorized by the Ministry of Sports Tunisia about their expectations, preferred communication channels, and thoughts on the importance of injury prevention. In Tunisia, we developed our questionnaire at the Ministry of Sports. Between May 2023 and January 2024, 250 practitioners who had been approved by the Ministry of Sports Tunisia were interviewed. Prior to face-to-face interviews, members of the Ministry of Sports Tunisia were required to read paper examinations. A phone call was made for incomplete forms and missing subjects. All the information was gathered by one individual.

An injury is characterized by "pain, discomfort, or an injury to the musculoskeletal system, occurring during the practice of sport (training or competition) and having had a negative impact on sports practice (reduction in practice, adaptation and incomplete practice, or cessation of practice)." Whether or not to seek medical counsel is up to the athletes. Every day in the evening, each athlete had to fill out a form that gathered information on possible injuries.

The study included 250 athletes, 150 of whom were women and 100 of whom were men. The average age of the study participants ranged from 18 to 22 years old. The quiz's response rate is 90.30%.

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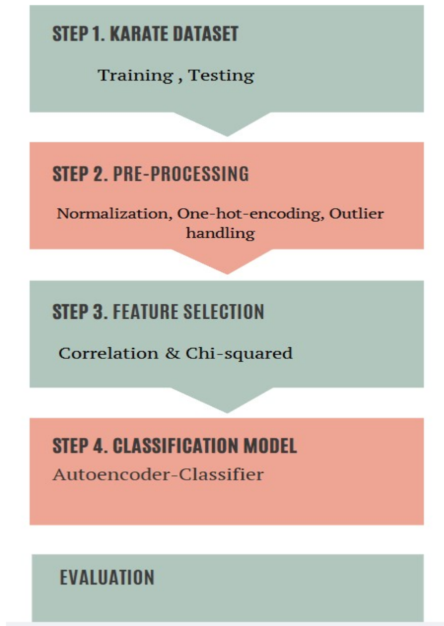

Figure 1. Workflow of the Proposed Approach

3.2. Data Pre-Processing

The purpose of the first preprocessing stage is to get the data ready for smooth processing by later modules. This procedure consists of three main steps: applying one-hot encoding, normalizing the data, and examining outliers.

- Analysis of outliers
  In this step, the z-score approach is used to identify the outliers. It entails locating data points that substantially depart from the dataset mean, frequently signifying the existence of extreme values.
  Use the formula given in reference [13] to find the z-score for each data point in the dataset. A data point is classified as an outlier if its z-score's absolute value exceeds a predetermined threshold. Then, by eliminating them from the dataset, these outliers may be controlled.
- Data normalization
  In this case, the StandardScaler method is used to rescale the data's numerical values. It entails transforming data so that its standard deviation equals one and its mean equals zero. The $x_{i,j}$ value of the itch feature in the data is converted to $z_{i,j}$ in Equation 1, where u_i and σ_i stand for the feature's mean and standard deviation, respectively.

$$z_{i,j} = \frac{x_{i,j} - u_i}{\sigma_i} \quad (1)$$

- One-Hot Encoding
  This encoding is used to represent categorical variables as binary vectors in the context of data preparation [14]. This procedure comprises transforming categorical data into a format that learning models can easily understand and handle.

3.3. Feature Selection

The process of choosing pertinent features to add to a dataset from the initial feature set is known as feature selection.

Feature selection seeks to minimize dimensionality while emphasizing the most valuable attributes in order to improve the effectiveness of machine learning models [15]. Two different statistical feature selection techniques are used in this study: the chi-square test is used to select 20 features with binary values from the preprocessed dataset, and Pearson correlation is used to select the top 20 continuous features from the processed data.

The linear relationship between the distance-related variables is evaluated using Pearson's correlation coefficient. Our feature selection process in this study uses Pearson's correlation. Pearson's correlation yields values between -1 and 1. A perfect negative correlation is denoted by a value of -1, a perfect positive correlation by a value of +1, and no linear relationship between the two variables by a value of 0 [16]. Rangkuti et al. provides the formula for determining Pearson's correlation coefficient between variables x and y [17].

A statistical technique known as the chi-square (χ^2) test can be used to determine whether two categorical variables are statistically linked. It is commonly used to examine data in contingency tables, where the variables are tabulated against each other. The test ascertains whether there is a significant deviation between the observed data distribution and the predicted distribution, assuming that the variables are independent. The definition of the Chi-square statistic can be found [18].

3.4. The Proposed AE Based Classifier

We developed an Autoencoder (AE) in our study that makes use of classifier capabilities. The input for the AE-classifier will be the features selected in the preceding step. Two fundamental processes make up the AE architecture: an encoder that lowers the dimensionality of the input data and a decoder that attempts to recover the original input from the compressed representation [19]. This autoencoder is skilled at identifying significant features in unlabeled data because it was trained using unsupervised learning. AE's primary structure is explained in Figure 2. In this case, x represents the input data, y the encoded data, and z the decoded data.

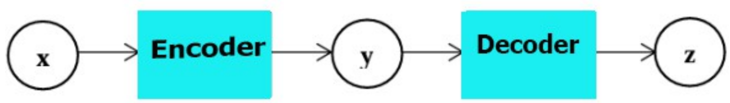

Figure 2. The Main Structure of AE

The suggested autoencoder framework (AE[40:30:40]) is shown in Figure 3(a). In particular, this autoencoder encodes a 40-dimensional feature representation (x) into a 30-dimensional vector (y) and then decodes it back to the feature space that was initially provided (z). The Root Mean Square Propagation (RMSprop) optimization approach is used in this study to train the AE[40:30:40] in an unsupervised fashion across 30 epochs with a batch size of 200.

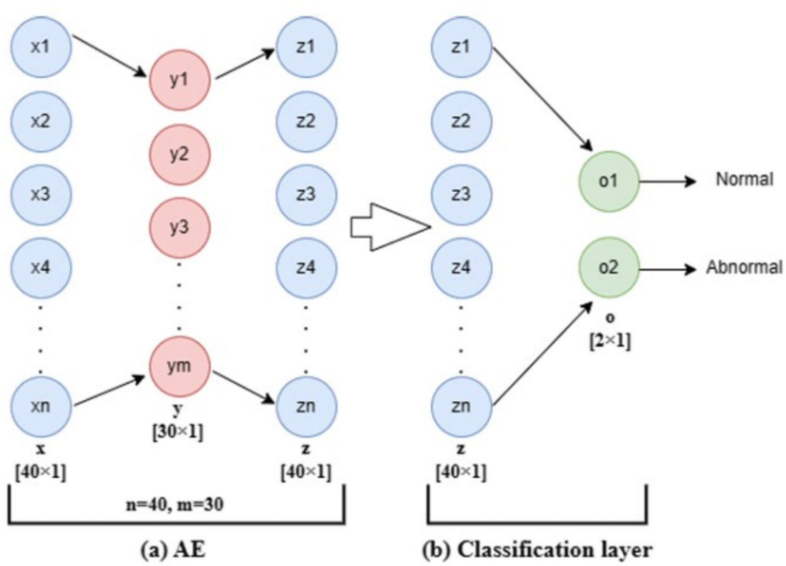

Figure 3. (a) The AE architecture and the suggested AE-based classification
(b) The classification layer that combines AE

The mean squared error (MSE) gauges how well the encoding and decoding processes worked. After AE[40:30:40] has been trained, the rebuilt features are fed into the classification layer, which uses the sigmoid activation function as its basis (classification layer, Figure 3(b)). The sigmoid layer is now modified for applications involving binary classification.

3.5. Evaluation and Discussion

The suggested approach is compared and assessed using accuracy, preci- sion, recall, F1-score.

1) Accuracy
It is the percentage of cases that are accurately categorized as all instances. Also referred to as detection accuracy, it is a useful performance metric that is only present in datasets that are balanced.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{2}$$

2) Precision (P)
It is the ratio of correctly predicted Attacks to all samples that were predicted as Attacks.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

3) Recall (R)
It shows the ratio of samples correctly recognized as assaults to samples that are attacks in fact. Another name for it is ”Detection Rate.”

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

4) F-measure (F)
The Precision and Recall harmonic mean is how it is de- fined. Put another way, it’s a statistical technique that evaluates a system’s accuracy by considering its recall and precision.

$$F - Measure = \frac{2.Precision.Recall}{Precision + Recall} \tag{5}$$

4. Finding and Discussion

We evaluated the performance of the suggested AE-classifier designs using a binary classification technique, where instances are classified as either "Normal" or "Abnormal," in order to determine the classifier's capacity to correctly distinguish between abnormal and normal attacks.

A machine running Windows 10 with a third-generation Intel Core i5 processor was used for the trials, and Python 3 was used to implement the suggested paradigm. The suggested classifier performed quite well in terms of accuracy (as indicated in Table 1), reaching a rate of up to 92.27%. The LDA, random forest, KNN, MLP, and SVM classifiers achieved accuracies of 92%, 91.86%, 91.29%, 91%, and 90.94%, respectively, yet this performance outperforms theirs.

Table 1. The Proposed Classifier’s and Other Classifiers’ Accuracy Results

Classifier	Accuracy
AE-classifier	92.27%
LDA	92%
Random forest	91.86%
KNN	91.29%
MLP	91%
SVM	90.94%

Table 2 represents a confusion matrix for a test set, allowing the performance of a binary classification model to be evaluated. Here are some key observations:

1) Matrix axes:
   - The lines represent the model predictions (Output)
   - The columns represent the real classes (Target).
2) Main values:
   - True positives (TP): 815381538153 (the model predicted "1" and the actual class was "1").
   - True negatives (TN): 399739973997 (the model predicted "0" and the actual class was "0").
   - False positives (FP): 918918918 (the model predicted "0" when the actual class was "1").
   - False negatives (FN): 100100100 (the model predicted "1" when the actual class was "0").
3) Performances:
   - Accuracy for class 0: 81.32% (correct predictions out of all predictions for class 0).
   - Accuracy for class 1: 98.79%.
   - Recall for class 0: 97.56%.
4) Recall for class 1: 89.88%.Error Analysis:
   - The model makes significantly more errors when classifying "0s":
   - 918 false negatives → This means that 18.68% of true "0s" are misclassified as "1s".
   - The "1" class is better detected, with only 1.21% false positives.
   - Overall, the model is better at detecting "1s" than "0s".

Table 2. The Suggested Classifier's Confusion Matrix (AE Classifier)

TESTING SET			
TARGET **OUTPUT**	0	1	**SUM**
0	3997 30.38%	918 6.97%	4915 **81.32%** **18.68%**
1	100 0.76%	8153 61.92%	8253 **98.79%** **1.21%**
SUM	4097 **97.56%** **2.44%**	9071 **89.88%** **10.12%**	12150/13168 **92.27%** **7.73%**

The model performs very well with an accuracy of 92.27%. it is important to adjust the classification threshold to reduce errors on the "0" class, use a class weight if class balance is important and try other models or techniques to improve "0" detection.

Table 3. Comparison with Other Works Available in The Literature

TYPE	ACC (%)
OUR MODEL	92.27%
Kamakis et al. [21]	66.04%
Jauhiainen et al. (Logistic Regression) [22]	65%
Jauhiainen et al. (Random Forest) [22]	63%
Henriquez et al. [23]	79%
Lovdal et al. [24]	78%
Van Eetvelde et al. [25]	87%
Majumdar et al. [26]	83.5%

Furthermore, as shown in Table 3, we compared the suggested classifier to recent approaches that have been used in injury detection research. The performance of the AE-classifier in a binary classification setting was the specific focus of our evaluation. Our examination of the data showed that, in terms of accuracy, the suggested AE-classifier outperforms the previously described studies.

5. Conclusion

In order to construct an injury detection system, we provide a classifier in this paper that is built on an Autoencoder (AE) architecture. The proposed method was tested using our dataset as a benchmark. Through the use of Pearson correlation and Chi-square tests, we were able to identify the most pertinent features, which were then fed into our AE architecture, which was specifically created with a single hidden layer including thirty units.

The AE-classifier was benchmarked against both conventional classifiers. The comparison's findings unequivocally show that the AE classifier fared better than any other approach, with an astounding accuracy rate of 92.27%. The study's findings have important practical applications, especially in the fields of sports science and injury prevention. This method can assist athletes, coaches, and medical professionals in tracking physical activity and identifying early indicators of damage by utilizing statistical feature selection and autoencoder-based classifiers.

Notwithstanding its encouraging findings, the study includes a number of shortcomings that need to be fixed in subsequent investigations. The model could be skewed toward particular movement patterns or sports. To guarantee wide application, more data from different sports and activities are needed. The quantity and quality of the input data have a significant impact on the model's efficacy. The robustness of the model would be enhanced with more datasets from a range of demographics and athletic skill levels. Autoencoders are good at detecting anomalies, however they are frequently not interpretable. It's still difficult to understand why an injury risk is indicated. Optimization is necessary to guarantee processing efficiency and minimal latency when implementing this strategy in real-time applications.

We intend to investigate the development of increasingly intricate Autoencoder (AE)-based architectures in our upcoming studies. Our goal is to look into how improving the AE architecture's hidden layer, unit, and activation function counts could improve the efficacy of injury detection. Additionally, our goal is to investigate ways to seamlessly integrate the injury detection system with real-time monitoring and reaction.

References

[1] Georeva_Acces, “Controle Sante Des Structures Ou Structural Health Monitoring (SHM pour les intimes): la fine frontière entre une structure saine ou endommagée,” *Georeva*, Dec. 19, 2023. [Online]. Available: https://georeva.eu/fr/controle-sante-structure. [Accessed: Oct. 21, 2024].

[2] X. Li *et al*., “Mechanics-informed autoencoder enables automated detection and localization of unforeseen structural damage,” *Nature Communications*, vol. 15, no. 1, Oct. 2024.

[3] J. Lin and H. Ma, “Structural Damage Detection Based on the Correlation of Variational Autoencoder Neural Networks Using Limited Sensors,” *Sensors*, vol. 24, 2024, Art. no. 2616.

[4] R. Cedeno-Moreno, L. A. Morales-Hernandez, and I. A. Cruz-Albarran, “A stacked autoencoder-based aid system for severity degree classification of knee ligament rupture,” *Computers in Biology and Medicine*, vol. 181, p. 108983, Aug. 2024.

[5] C. Silver and T. Akilan, “A Novel Approach for Fall Detection Using Thermal Imaging and a Stacking Ensemble of Autoencoder and 3D-CNN Models,” in *Proc. IEEE Canadian Conf. Electr. Comput. Eng. (CCECE)*, Regina, SK, Canada, pp. 71–76, 2023.

[6] T. Nielsen, “Sports datasets for data modeling, visualization, predictions, Machine-Learning.” [Online]. Available: https://sports-statistics.com/sports-data/sports-data-sets-for-data-modeling-visualization-predictions-machine-learning/. [Accessed: Oct. 21, 2024].

[7] Y. Gautam and H. Jebelli, “Autoencoder-based Photoplethysmography (PPG) signal reliability enhancement in construction health monitoring,” *Automation in Construction*, vol. 165, pp. 105537, Sep. 2024.

[8] Y. Gautam and H. Jebelli, “Autoencoder-based Photoplethysmography (PPG) signal reliability enhancement in construction health monitoring,” *Automation in Construction*, vol. 165, 2024.

[9] H. Wang, Z. Han, X. Xiong, X. Song, and C. Shen, "Enhancing Yarn Quality Wavelength Spectrogram Analysis: A Semi-Supervised Anomaly Detection Approach with Convolutional Autoencoder," *Machines*, vol. 12, 2024.

[10] C. Dindorf *et al*., "Enhancing biomechanical machine learning with limited data: generating realistic synthetic posture data using generative artificial intelligence," *Front. Bioeng. Biotechnol.*, vol. 12, Feb. 2024.

[11] X. Ye, Y. Huang, Z. Bai, and Y. Wang, "A novel approach for sports injury risk prediction: based on time-series image encoding and deep learning," *Front. Physiol.*, vol. 14, Dec. 2023.

[12] M. A. Javed *et al*., "Leveraging Convolutional Neural Network (CNN)-based Auto Encoders for Enhanced Anomaly Detection in High-Dimensional Datasets," *Engineering, Technology & Applied Science Research*, vol. 14, no. 6, pp. 17894–17899, Dec. 2024.

[13] N. B. Chikodili, M. D. Abdulmalik, O. A. Abisoye, and S. A. Bashir, "Outlier detection in multivariate time series data using a fusion of K medoid, standardized euclidean distance and Z-score," in *Proc. Int. Conf. Inf. Commun. Technol. Appl.*, pp. 259–271, 2020.

[14] A. Y. Hussein, P. Falcarin, and A. T. Sadiq, "Enhancement performance of random forest algorithm via one hot encoding for IoT IDS," *Periodicals of Engineering and Natural Sciences*, vol. 9, no. 3, pp. 579–591, 2021.

[15] R. Zebari, A. Abdulazeez, D. Zeebaree, D. Zebari, and J. Saeed, "A comprehensive review of dimensionality reduction techniques for feature selection and feature extraction," J. Appl. Sci. Technol. Trends, vol. 1, no. 2, pp. 56–70, 2020.

[16] Y. Bae and H. Lee, "Sentiment analysis of twitter audiences: Measuring the positive or negative influence of popular twitterers," J. Am. Soc. Inf. Sci. Technol., vol. 63, no. 12, pp. 2521–2535, 2012.

[17] F. R. S. Rangkuti, M. A. Fauzi, Y. A. Sari, and E. D. L. Sari, "Sen timent analysis on movie reviews using ensemble features and pearson correlation-based feature selection," in 2018 International Conference on Sustainable Information Engineering and Technology (SIET), 2018.

[18] I. S. Thaseen, C. A. Kumar, and A. Ahmad, "Integrated intrusion detec tion model using chi-square feature selection and ensemble of classifiers," Arab. J. Sci. Eng., vol. 44, pp. 3357–3368, 2019. [19] J. Zhai, S. Zhang, J. Chen, and Q. He, "Autoencoder and its various variants," in 2018 IEEE international conference on systems, man, and cybernetics (SMC), 2018, pp. 415–419.

[20] S. Kampakis, *Predictive Modeling of Football Injuries*, Dept. of Computer Science, Univ. College London, London, U.K., Apr. 2016.

[21] S. Jauhiainen et al., "New Machine Learning Approach for detection of injury Risk Factors in young Team sport Athletes," International Journal of Sports Medicine, vol. 42, no. 02, pp. 175–182, Sep. 2020.

[22] M. Henriquez, J. Sumner, M. Faherty, T. Sell, and B. Bent, "Machine learning to predict lower extremity musculoskeletal injury risk in student athletes," Frontiers in Sports and Active Living, vol. 2, Nov. 2020.

[23] S. S. Lövdal, R. J. R. D. Hartigh, and G. Azzopardi, "Injury prediction in competitive runners with machine learning," International Journal of Sports Physiology and Performance, vol. 16, no. 10, pp. 1522–1531, Jan. 2021.

[24] H. Van Eetvelde, L. D. Mendonça, C. Ley, et al., "Machine learning methods in sport injury prediction and prevention: a systematic review," *J. Exp. Orthop.*, vol. 8, no. 27, 202.

[25] R. Beal, T. J. Norman, and S. D. Ramchurn, "Artificial intelligence for team sports: a survey," The Knowledge Engineering Review, vol. 34, Jan. 2019.