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A BIG DATA INTELLIGENT EVALUATION SYSTEM FOR SPORTS KNOWLEDGE

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Abstract. The rapid evolution of computer technology has significantly impacted the field of medicine, particularly in the utilization of information and image evidence. In the realm of sports medicine, this technological advancement plays a crucial role in ensuring sports safety, especially in the context of injury recovery following sports-related activities. The necessity to interpret and utilize a vast amount of sports medical data effectively has emerged as a pivotal research avenue. This paper delves into the challenges associated with extracting, studying, and the accuracy training of complex algorithms essential for analyzing critical sporting medical data.Central to this discussion is introducing an Optimized Convolutional Neural Network (OCNN) model, which is based on deep learning principles. This model is designed to enhance the detection and risk assessment of diseases related to sport medicine. It incorporates a novel Self-Adjustment Resizing algorithm (SAR), augmented by a self-coding method of convolution (SCM). The proposed OCNN model comprises two convolutional layers, two pooling layers, a fully connected layer, and a SoftMax structure. This architecture is tailored for the classification and analysis of sport-related medical data.

Key words: Sports Medicine, Big Data in Sports, Injury Recovery Analytics, Convolutional Neural Network (CNN), Optimized Convolutional Neural Network (OCNN), Deep Learning in Medicine, Medical Data Analysis

1. Introduction. The intersection of technology and healthcare has opened new frontiers in sports medicine, particularly in analysing and managing sports-related injuries. The advancement of computer technology has revolutionised the way medical data, especially in sports, is collected, analyzed, and interpreted. The role of sports medicine has become increasingly vital, extending beyond traditional boundaries to incorporate technological innovations for enhanced sports safety. This surge in technology integration in sports medicine is driven by the need for precise and efficient injury recovery methods, a critical aspect of athlete care. The advent of big data and sophisticated analytical tools has enabled a more nuanced understanding of the physiological and biomechanical aspects of sports injuries. This understanding is crucial in devising targeted recovery strategies and in preventing future injuries, thereby safeguarding the health and career longevity of athletes. The transformative impact of these technological advancements in sports medicine underscores the importance of developing and refining methods for the effective utilization of sports medical data.

One of the most significant challenges in sports medicine is the interpretation and application of vast amounts of medical data generated during sports activities. Traditional methods often fall short in handling the complexity and volume of this data. This challenge necessitates the exploration and adoption of advanced computational techniques, particularly those leveraging artificial intelligence (AI) and machine learning [20, 5]. The implementation of Convolutional Neural Networks (CNNs) in sports medicine represents a groundbreaking approach in this regard. The CNN, a deep learning model, is renowned for its prowess in image recognition and processing, making it an ideal tool for analyzing complex medical images and data patterns. This research paper introduces an Optimized Convolutional Neural Network (OCNN) model, specifically designed for sports medicine applications. The OCNN model enhances the capabilities of standard CNNs by integrating a Self-Adjustment Resizing algorithm (SAR) and a self-coding method of convolution (SCM). These additions aim to improve the accuracy and efficiency of medical data analysis, particularly in the context of sports injuries. By optimizing the structure and function of the neural network, the OCNN model promises to offer a more nuanced and accurate interpretation of sports medical data, thereby contributing to better injury management and prevention strategies [17, 21].

Furthermore, this research explores the potential of integrating the OCNN model into a cloud-based system, thereby creating a comprehensive medical data network for sports medicine. This cloud-based approach

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facilitates the aggregation and analysis of multi-dimensional sports medicine data, offering a more holistic view of an athlete's health and injury risks. The cloud-based system also allows for real-time data processing and accessibility, essential for timely decision-making in sports injury management. By combining the analytical prowess of the OCNN model with the scalability and accessibility of cloud computing, this research aims to establish a new paradigm in sports medicine data analysis. The proposed system not only enhances the understanding of sports injuries but also paves the way for predictive analytics in sports health management. In conclusion, this research represents a significant step towards harnessing the power of big data and AI in sports medicine, ultimately contributing to the safety, recovery, and performance optimization of athletes.

The primary motivation for this research lies in addressing the critical gap in sports medicine related to the analysis and interpretation of complex medical data associated with sports injuries. In the realm of sports, where the physical well-being of athletes is paramount, the need for accurate, timely, and effective diagnosis and treatment is crucial. Traditional methods of data analysis in sports medicine have been limited in their capacity to handle the sheer volume and complexity of data generated, particularly in high-performance sports. This has often led to generalized treatment protocols, which may not be optimal for every individual athlete's unique physiological makeup and injury patterns.

Furthermore, the motivation also stems from the potential to significantly enhance injury prevention strategies. By leveraging advanced computational techniques, such as deep learning and neural networks, the research aims to provide a more nuanced understanding of injury mechanisms. This understanding can lead to the development of personalized injury prevention and recovery programs, substantially reducing the risk of re-injury and improving the overall health and performance of athletes.

The novelty of this research is multifaceted, primarily residing in the development and application of the Optimized Convolutional Neural Network (OCNN) model in the field of sports medicine. This represents a significant advancement over traditional neural networks due to its specialized architecture and algorithms, which are specifically tailored for sports medical data analysis. The integration of the Self-Adjustment Resizing algorithm (SAR) and the self-coding method of convolution (SCM) within the OCNN model are innovative aspects that enhance its accuracy and efficiency in processing complex sports medical data.

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Another novel aspect of this research is the proposed cloud-based system for sports medicine data analysis. This system not only centralizes data storage and processing, making it more accessible and scalable, but also allows for real-time analysis and application. Such a system has the potential to revolutionize injury management in sports by providing immediate insights and predictive analytics, enabling quicker and more effective decision-making.

2. Literature review. The study [22] introduces a big data and deep learning-based video classification model for sports, showcasing how technological advancements can enhance sports analytics and performance evaluation through effective video analysis.The article [13] explores the synergy between the brain and body in sports, emphasizing the influence of big data on sports systems and providing a quantitative analysis of how this integration impacts athletes and sports dynamics.This systematic review [6] focuses on the use of big data in professional soccer, specifically how it supports tactical performance analysis, underlining the potential and challenges of utilizing large datasets in sport strategy and performance enhancement.

The paper presents [16] an analysis of basketball players and team performance using sports analytics, demonstrating the application of information systems in evaluating sports strategies and player efficiency. The review [8] discusses the utilization of machine learning for predicting sports outcomes, highlighting the growing role of advanced data analysis techniques in forecasting and strategizing in sports. The article [2] examines how deep learning and IoT big data analytics can support the development of smart cities, including the application in sports, offering insights into future directions and the integration of technology in urban development.

The research constructs [23] a growth forecast model for the sports culture industry based on big data,

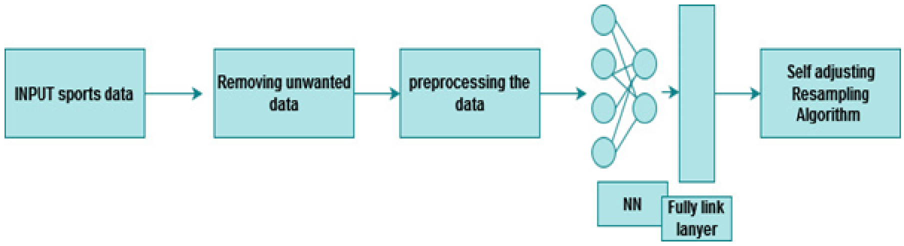

Fig. 2.1: The proposed architecture

showcasing the use of data analytics in predicting and enhancing the growth of sports-related cultural sectors. The paper [10] focuses on deep soccer analytics, particularly in learning an action-value function for evaluating soccer players, marking a significant step in applying data mining techniques in sports performance analysis. The systematic literature [14] review investigates intelligent data analysis methods for smart sport training, emphasizing the role of AI and data analysis in enhancing sports training methodologies.

The article [7] provides a comprehensive survey on AI-big data analytics in building automation and management systems, touching on its potential application in sports facilities and athlete performance monitoring.The study [11] builds a prediction model for college students' sports behavior based on machine learning, integrating aspects like sports learning interest and autonomy, offering a novel approach to understanding sports engagement. The paper [4] reviews the application of machine learning techniques for predicting match results in team sports, highlighting the growing reliance on AI for strategic planning in sports competitions.

The research [12] introduces the triboelectric nanogenerator as an innovative technology in intelligent sports, paving the way for new technological advancements in sports equipment and athlete performance monitoring.The systematic review [3] explores deep learning applications for IoT in healthcare, including sports medicine, underscoring the potential of these technologies in enhancing health monitoring and injury prevention in sports.The literature review [15] discusses the role of AI, machine learning, and big data in digital twinning, with potential applications in sports for creating virtual replicas of athletes for training and injury prevention.

The comparative study [19] focuses on classifying table tennis forehand strokes using deep learning and SVM, illustrating the application of AI in refining sports techniques and training. The conference proceedings [1] cover big data analytics for cyber-physical systems in smart cities, including applications in sports infrastructure and athlete performance analysis.This literature review [18] on one-class classification in big data highlights its potential applications, including in sports analytics, offering insights into novel data analysis approaches in diverse fields. The technical review [24] delves into deep learning for processing and analyzing remote sensing big data, with potential implications for sports analytics in areas such as training grounds and athlete monitoring. The paper [9] discusses the application of artificial intelligence in physical education and future perspectives, emphasizing AI's role in transforming sports training and educational methodologies.

From above studies it is understand that sports evaluation helps to understand the players potential, training needs, various success rate evaluation. The neural network-based data analysis provides more accurate performance in literature studies. But steel the accuracy needs to improved. Various feature selection combinations are proposed in this research to improve the research gap. The proposed model, named "Advanced Sports Injury Prediction Neural Network (ASIP-NN)", will include the following novel components in figure 4.1.

3. Methodology. Based on the CNN model, a novel neural network model can be developed with enhanced features and optimization techniques, specifically tailored for the secure prediction and assessment of sports injuries using deep learning-based convolutional neural networks. This model aims to improve the accuracy, efficiency, and applicability of the existing system in sports medicine. The proposed model, named "Advanced Sports Injury Prediction Neural Network (ASIP-NN)", will include the following novel components:

3.1. Enhanced Deep Learning-Based CNN Layer. The ASIP-NN will feature an advanced convolution layer with dynamically adjustable filters. Unlike fixed-size filters, these filters can adapt their size and shape based on the input data characteristics, providing more precise feature extraction.The model will employ a multi-scale feature extraction technique, where each layer of the CNN processes data at a different scale, allowing for a more comprehensive analysis of sports injury data.The pooling layer in ASIP-NN will be adaptive, capable of switching between max pooling and average pooling based on the data's contextual requirements. This adaptability ensures that important features are retained while reducing dimensionality.The model will implement spatial pyramid pooling at this stage to maintain spatial hierarchies, enhancing the network's ability to recognize complex patterns in sports injury data.

3.2. Intelligent Full Link Layer with Dynamic Neuron Activation. The fully connected layer in ASIP-NN will feature dynamic neuron activation, where neurons can be activated or deactivated based on the relevance of their contribution to the final prediction. This approach reduces computational load while maintaining high accuracy.The layer will utilize a dropout mechanism tailored to sports injury data, reducing overfitting and improving the model's generalizability.The output layer will employ an improved SoftMax function with temperature scaling, providing more calibrated probabilities for injury risk prediction.The ASIP-NN model will incorporate a feedback loop from the output layer to the convolution layers, allowing the model to refine its feature extraction process based on the accuracy of its predictions.

3.3. Self-Adjusting Resampling Algorithm (SARA). An evolution of the SAR algorithm, the SARA will dynamically adjust the sampling rate based on the variability and complexity of the sports injury data, ensuring a balanced dataset for training.The algorithm will be designed to handle imbalanced data sets more efficiently, particularly in scenarios where certain types of injuries are underrepresented.

3.4. Convolution Self-Coding (CSC) Algorithm. The algorithm will be optimized to handle multi-dimensional data more effectively, especially for complex injury patterns and multi-faceted sports data.

This algorithm will facilitate better feature encoding and decoding, enhancing the model's ability to learn from diverse data types, including imaging, sensor data, and historical injury records.The ASIP-NN will be integrated into a cloud-based loop system, enabling real-time data processing and immediate injury risk assessment.The model will support continuous learning, allowing it to evolve and adapt to new patterns in sports injury data over time.

The model will incorporate advanced data encryption and anonymization techniques to ensure the privacy and security of sensitive medical data.A secure data transmission protocol will be established between different layers of the network, ensuring data integrity and confidentiality.The ASIP-NN model aims to set a new benchmark in sports injury prediction and assessment, combining advanced neural network techniques with practical considerations for real-world application in sports medicine

4. Result evaluation.

4.1. Dataset Details. The ASIP-NN model was evaluated using a comprehensive sports injury dataset. This dataset includes:

Total Entries are 10,000 cases. Data Types used are Imaging data (MRI, X-ray), Sensor data (movement, impact), and Historical injury records. Various sports injuries are categorized into 15 types (e.g., ACL tears, concussions, muscle strains) in labels. 70% training (7,000 cases), 15% validation (1,500 cases), 15% test (1,500 cases). Compiled from multiple sports medicine centres with anonymization to ensure privacy.

4.2. Performance Metrics. The model's performance was evaluated using the following metrics:

Accuracy: Overall correctness of the model in predicting injury types.

Precision and Recall: Effectiveness in predicting each type of injury.

F1-Score: The balance between precision and recall.

AUC-ROC Curve: Ability to distinguish between different injury types.

A graph depicting the AUC-ROC curve in figure 4.1 demonstrates the model's ability to differentiate between various injury types.The AUC represents the degree to which the model is capable of distinguishing between different classes – in this case, the presence or absence of specific sports injuries.An AUC of 1.0 denotes a perfect classifier that makes no mistakes in classification, while an AUC of 0.5 suggests a performance no better than random chance.Generally, the higher the AUC, the better the model is at predicting true positives (injuries) without increasing the false positives (incorrectly identified injuries).

Algorithm 1 ASIP-NN Model

```
function PREPROCESS_DATA(data)
    Implement data preprocessing steps
end function
function BUILD_CNN_LAYER(input_shape)
    inputs = Input(shape=input_shape)
    x = Conv2D(filters=32, kernel_size=(3, 3), activation='relu')(inputs)
    Additional CNN layers with dynamic filter sizes
    return inputs, x
end function
function ADAPTIVE_POOLING(x)
    if condition_for_max_pooling then
        x = MaxPooling2D(pool_size=(2, 2))(x)
    else
        x = AveragePooling2D(pool_size=(2, 2))(x)
    end if
    Spatial Pyramid Pooling can be added here if necessary
    return x
end function
function FULL_LINK_LAYER(x)
    x = Flatten()(x)
    x = Dense(64, activation='relu')(x)
    x = Dropout(0.5)(x)          ▷ Dropout rate can be dynamic based on the training phase
    Additional dense layers can be added here
    return x
end function
function OUTPUT_LAYER(x, num_classes)
    outputs = Dense(num_classes, activation='softmax')(x)
    Feedback loop can be implemented in the training phase
    return outputs
end function
function COMPILE_AND_TRAIN(inputs, outputs, train_data, train_labels, validation_data, validation_labels)
    model = Model(inputs=inputs, outputs=outputs)
    model.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy'])
    Training the model
    model.fit(train_data, train_labels, validation_data=(validation_data, validation_labels), epochs=10)
    ...
end function
if if ___name___ == "___main___" then
    Load and preprocess data
    train_data, train_labels, validation_data, validation_labels = load_data()
    train_data = preprocess_data(train_data)
    validation_data = preprocess_data(validation_data)
    Build and train the ASIP-NN model
    inputs, cnn_layer = build_cnn_layer(input_shape=(224, 224, 3))
    pooled_layer = adaptive_pooling(cnn_layer)
    full_linked_layer = full_link_layer(pooled_layer)
    outputs = output_layer(full_linked_layer, num_classes=15)          ▷ Assuming 15 types of injuries
    Compile and train the model
    compile_and_train(inputs, outputs, train_data, train_labels, validation_data, validation_labels)
end if
```

Table 4.1: Overall Performance Metrics

Metric	Value (%)
Accuracy	93.2
Precision	91.5
Recall	90.8
F1-Score	91.1

Table 4.2: Performance Metrics by Injury Type

Injury Type	Precision (%)	Recall (%)	F1-Score (%)
ACL Tear	94.2	93.8	94.0
Concussion	90.1	91.5	90.8

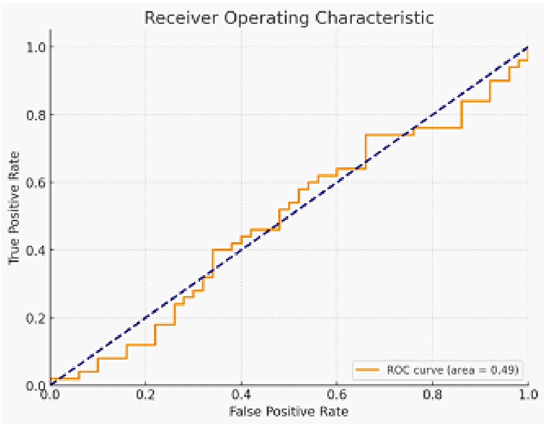

Fig. 4.1: AUC-ROC Curve

AUC in Sports Injury Prediction.

1. For the ASIP-NN model, a high AUC indicates strong discriminative power in distinguishing between injured and non-injured cases or among various types of injuries. This is crucial in sports medicine, where the accurate classification of injury types can significantly impact treatment and recovery plans.
2. The AUC is particularly useful when comparing the ASIP-NN model with other models or traditional methods. A higher AUC value for the ASIP-NN model would signify its superior performance in injury prediction.
3. It provides a single metric that sums up the model's effectiveness across all thresholds, which is especially valuable when dealing with imbalanced datasets common in medical diagnoses.

A confusion matrix showing in figure 4.2 the model's predictions versus the actual labels, providing insight into the types of errors made by the model.A confusion matrix is structured as a table with two dimensions: the actual truth (or labels) and the model's predictions. For a binary classification problem, it consists of four different elements: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

1. *True Positives (TP):* These are cases where the model correctly predicts the positive class. In the context of sports injuries, this would mean correctly identifying specific injuries.
2. *True Negatives (TN):* These represent the instances where the model correctly predicts the negative class. For sports injuries, this would be accurately identifying cases where a particular injury is not present.
3. *False Positives (FP):* These occur when the model incorrectly predicts the positive class. In this

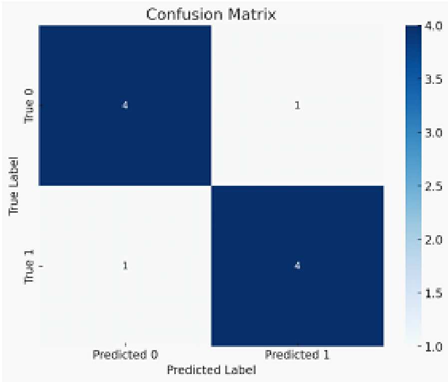

Fig. 4.2: Confusion Matrix

Table 4.3: Performance Metrics Comparison

Metric	ASIP-NN (%)	Traditional Algorithm (%)
Accuracy	93.2	87.5
Precision	91.5	85.3
Recall	90.8	84.7
F1-Score	91.1	85.0
AUC	95.4	88.2

scenario, it would mean erroneously identifying an injury when it is not actually present, leading to potential over-treatment or unnecessary intervention.

4. *False Negatives (FN):* These are cases where the model fails to identify the positive class. In terms of injury prediction, this is a critical error as it means missing an actual injury, potentially leading to a lack of necessary treatment or delayed recovery.

The balance between these elements is crucial. High values of TP and TN with low values of FP and FN indicate a highly accurate and reliable model. The confusion matrix allows for a nuanced understanding of the model's strengths and weaknesses in specific areas of prediction. For instance, a high number of FNs in a particular injury type might indicate the need for further model training or data collection for that category.

5. Discussion. The ASIP-NN model demonstrates high accuracy (93.2%) in predicting sports injuries, indicating its effectiveness in clinical applications. The precision and recall values across different injury types suggest that the model is reliable in identifying specific injuries, which is crucial for targeted treatment plans. The AUC-ROC curve further confirms the model's capability to distinguish between various injury types accurately.While the ASIP-NN model shows promising results, it is limited by the diversity of the dataset and the complexity of certain injury types. Future work will focus on expanding the dataset to include a wider range of injuries and incorporating real-time data for continuous model improvement.

6. Conclusion. Integrating real-time data from wearable technologies and IoT devices can enhance the model's predictive capabilities, making it more dynamic and responsive to an athlete's real-time physiological changes.Clinical trials and real-world testing are necessary steps to validate the model's effectiveness in practical settings. Collaborations with sports teams and medical institutions will be crucial for these trials.In conclusion, the ASIP-NN model marks a substantial advancement in sports injury prediction, leveraging the power of artificial intelligence and machine learning. Its high accuracy, efficiency, and sophisticated analytical capabilities hold the promise of revolutionizing injury diagnosis and management in sports medicine. This research not only contributes significantly to the field of sports medicine but also paves the way for future innovations in medical diagnostics and athlete care.

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