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RESEARCH ARTICLE

Unveiling the Captivating Biomechanics of Elite Sports Dance: A Deep Dive into the Kinetics 600 Dataset

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This study applies biomechanical analysis to elite sports dance using the Kinetics 600 dataset, aiming to improve the categorization of dance forms. Employing machine learning techniques, particularly Random Forest, we classified dance activity types and identified subtle biomechanical differences. The dataset underwent preprocessing to define inherent aspects, followed by training and testing classification models using accuracy, precision, recall, and F1 scores as performance metrics. Results showed an overall accuracy of 76%, with some movements exhibiting lower classification metrics. These findings highlight the biomechanical properties of certain dance movements that current models struggle to quantify effectively. The distinctions between precise movements suggest missing or inadequately represented biomechanical signatures, necessitating further research. This study underscores the importance of biomechanical analysis in refining training methods, improving efficiency, and reducing injury rates in sports dance. Future work will explore combining wearable technology and machine learning to collect enhanced biomechanical data for improved differentiation of dance movements.

INTRODUCTION

Universally dance elite sports, the grace, physical exertion, and precision required to achieve great results are extraordinary. This highly skilled sport requires not just artistic reflection but also flawless biomechanical execution. Understanding the complex biomechanical elements behind the performance of the elite level can provide important insights into injury prevention [1], performance improvement [2], and athletic training [3]. As dancers in elite sports push the restriction for human movement, biomechanical analysis is critical to examining the complex connection of force, body dynamics and motions that contribute to high performance [4]. Biomechanics is the science of movement and strength, which provides a quantitative perspective to analyse physical fitness in dance sports. With the technology of biomechanical modelling and motion capture, it is feasible to examine how dancers integrate their bodies in freedom, handle external forces, and control balance to perform precise movements. This intuition can teach training programs, allowing coaches and athletes to improve technique, decrease injury risk, and improve general athletic performance. However, analysing and capturing biomechanical data needs specialized datasets as well as computing techniques which can process large quantity of information. The Kinetics-600 dataset is one such dataset that allows an in-depth study of the biomechanics of dance elite sports [5]. The k600 dataset gives the opportunity to examine biomechanical elements of movement dance by several deep learning [6] and machine learning techniques [7], which can assist in identifying movement patterns and relationships that traditional analysis methods cannot reveal. Biomechanics is gradually becoming an important area of dance research, specifically in knowing the complex relationship between movement and performance outcomes. Applying the principles of movement biomechanics to dance not only improves performance but also plays an important role in damage prevention. Dance is a complex art form that transcends mere motion and embodies the complex interface of biomechanics, emotional expression, and aesthetics. Biomechanics, the research of the movement and strength of an organism, plays an important role in the study of dance, providing valuable insights into improving performance and reducing the risk of injury. A study [8] explores the field of sports biomechanics aiming to enhance performance and reduce injury rates in athletes. This study utilizes a movement biomechanics approach to assess a dancer's movements, performance needs, and injuries, *adjusting* to the special needs of different dance forms. Movement biomechanics literature and early work focused on dancers has been drawn, spanning a variety of dance genres and performers. Dance biomechanics provides important insights into enhancing performance of the dancer and understanding injury avoidance by addressing issues remarkable to the dance field. More research is needed to increase biomechanics understanding for various dance forms and increase injury avoidance techniques. This work sets the stage for further exploration into dance biomechanics, highlighting the need for continued work to strengthen our understanding of various dance modes and enhances safety practices. The purpose of this study was to study the biomechanics of elite sport dance utilizing the Kinetics-600 dataset, this gives a treasure of data to examine dancer movements as well as understand the physiological claim of different dance forms. Insights gained from [8] have greatly advanced the understanding of injury prevention, demonstrating that while numerous questions in the biomechanics of dance have been *managed*, further research into the biomechanics of different dance styles is needed to increase our perception of biomechanics.

The development of dance biomechanics research by technological progress and methodological creation has been remarkable, especially in the past few decades. The authors [2] reviewed the literature on biomechanical research in dance, focusing on motor strategies and dance movements. Involves the use of electromyography (EMG), motion analysis, force plates, or physics-based techniques to examine dance movements. A total of 89 papers, abstracts, and thesis were reviewed, completing a variety of dance movements including plié, relevé, passé, degage, grande batement and others. Elite dancers demonstrate superior movement strategies, and despite corresponding training backgrounds, there are significant differences between dancers. Teacher advice often conflicts with biomechanical approaches. Future research needs to explore better teaching techniques consistent with biomechanical ethics and enhance measurement instruments and research methods. This variability suggests that faculty recommendations often dispute with biomechanical approaches, indicating the demand for research focused on aligning instructional approaches with biomechanical ethics. In the setting of technological advances, the evolution of movement analysis structures and computer replication modelling beyond the last 50 years has been of great significance in sports and the biomechanics of dance. The study [9] reviewed development in motion analysis systems and computer simulation modelling of sports movements over the past fifty years. The importance and relevance of functional variability of sports techniques have become increasingly recognized. It conceals advances in motion trapping, computer simulation, and the increasing utilisation of large subject libraries for better data analysis. The research covers a wide scope of sports, from particular performance to player-on-player impacts, using both general and individual special parameters. As individual models are increasingly used, a deeper understanding of motion mechanics and performance optimization is gained. The significance of levelling model complexity as well as functionality is emphasized. Future research can be marker-less motion capture, and improvements in individual specific model parameters, with a greater focus on motor control elements in the analysis of sports methods. Care needs to be taken to avoid overreliance on automated ways without a basic understanding. Despite advances, the traditional paradigm of implemented sports biomechanics study still faces limitations, especially in optimizing the technique of individual athletes. A study [10] analyses the effectiveness and highlights issues with, conventional paradigms in applied sports biomechanics work and comments on their load to upgrade techniques of particular athletes. It criticizes group-based analyses for hiding individual differences and discusses the challenges faced by computer simulation approaches in forecasting performance under competitive pressure. This article cites both empirical as well as theoretical studies of biomechanics sports but highlights the uncertainty surrounding many of the findings about successful vs. unsuccessful performance. Current methods struggle to reliably identify performance-improving techniques, boosting concerns regarding their utility in real-world sports settings. Researchers are advised to exercise caution when explaining biomechanical data, considering individual distinctions and limitations of existing models. Future work can focus on enhancing athlete-specific perceptions and practical employment. Special focus on sports ballroom dancing, the researchers [11] carried out a theoretical and methodological analysis of literature engaged in biomechanical elements of dance sports, Reviewing the moves of two special dances. They analyse and identify the biomechanical properties of sports ballroom dance movements to improve motor performance and skill development. The study was derived from biomechanical data on dance movements, with a specific focus on the knee joint extent during the dance phase. Biomechanical analysis assists improve training techniques for both fresher and experienced dancers by providing an in-depth understanding of movement mechanics to improve performance and method. Future research may focus on incorporating biomechanical investigation into expansive training systems and exploring its application in different types of dance to further improve skills. Additionally, an important study on the movement and choreographic characteristics of tango provides further insights. The researchers [12] investigate the movement and choreography characteristics between 4 distinct quality groups in tango. Their study included an analysis of total time, average speed and direction changes in international dance pair competitions. The study quantified measures like direction change and movement speed, showing significant differences in movement speed between qualitative groups. These revelations lay the foundation for further work aimed at providing biomechanical insights into choreography and dancer preparation. The interchange of HAR (human action recognition) and biomechanics provides additional chances to improve dance analysis. Studies like [13] and [14] on action recognition, and human behaviours based on videos were a familiar approach, and more complex action recognition works guided through successful object detection and image classification in videos and images were explored. The studies investigated the complexities of realizing actions in different movement contexts, highlighting the potential use of the HAR structure in dance. Advances in video motion recognition methods explain how these technologies can improve the evaluation of dancers' movements, permitting more elegant assessments of performances and a better knowledge of the implicated biomechanics. An introduction to the Video Badminton dataset highlights the significance of comprehensive datasets for enhancing action recognition techniques [15].

Deep learning CNN technique has been used. Although the focus of this study is badminton, the methods and insights can be applied to dance, further improving the discussion of biomechanical analysis. The attainability of high-quality datasets allows researchers to capture subtle movements and improve analysis techniques, eventually helping to better understand and perform dance. Additionally, the researchers [16] explore advancements in DNN (deep neural networks) that have contributed to near-perfect results for various computer vision issues, such as face recognition, pose estimation, and object recognition. They address a multi-view outdoor acting recognition dataset to solve the difficulties of human action detection from different angles (especially aerial perspectives). The dataset is estimated utilizing a two-stream CNN with enhanced non-linear feature representation and a pooling scheme called kernelized rank pooling. 20 classes of human actions, 2324 video clips, as well as 503086 frames were resized and cropped to preserve the actual aspect ratio of the human body. The basic action recognition of this dataset accuracy was 74%, determining its potential usefulness in multiple research areas such as surveillance, situational awareness, and action recognition. This study suggests the demand for more detailed datasets covering different viewpoints to further improve action recognition performance. Nonverbal communication among dancers is a different important area of research worth exploring. A study by [17] on how expert, as well as non-expert performers, interact in contemporary dance improvisation shows that expert dancers are in a performance mode, described by higher motor control as well as subtle interactions. The ability of professional dancers to integrate movements without direct eye contact demonstrates the modern skills needed for effective cooperation in dance. Deriving such dynamics can improve training methods that emphasize the significance of body terminology and peripheral attention in developing a coherent dance performance. Finally, the study of injury mechanisms is an important aspect of biomechanics dance research. The research by [1] Biomechanical factors leading to meniscus injury throughout dynamic movements such as grand plié are specifically addressed. The authors emphasize the demand for comprehensive 3-dimensional kinematic assessment to well know how excessive motion and rotational forces contribute to injury. This study highlights the importance of using advanced measurement equipment, like force plates, photoelectric cameras, to estimate the factors of biomechanical at play in dance movements. This present study not just bridges the opening between dance sports and biomechanics, but also emphasizes the potential of machine learning techniques to advance sports science. By using random forests to delve deeper into the K600 (kinetics-600) dataset we intent to discover secret biomechanical patterns which can teach training and performance improvement strategies for the elite sports dancers. The results of this research will bestow to the thriving knowledge body on movement dance biomechanics, also prove the potential of ML to revolutionize the way movement performance is understood.

METHODOLOGY

The data collected in this work is from the Kinetics 600 which includes a vast array of human motions [18]. For this study, the lens is turned specifically on videos associated with the elite sporting discipline of dance and the selected subset of 29,086 processed videos from this list is used for further examination. Every video in this subset is linked with a label that corresponds to the activity class and the labels include various forms of dance and other sports activities.

These videos are now of the same format, and each of the vis-à-vis videos has been resized to have a frame size of 6 x 6 pixels in size. Besides, each video has at most 16 frames so that the dataset is more uniform and to minimize the computational time while analysing and modelling. Since the activity classes represent actual labels for the classification, different forms of sports and related movements in the dataset are distinguishable. These labels are used to build training models used in classifying or predicting the activities captured in the videos [18].

Figure 1. displays the videos in the kinetics600_5per and kinetics400_5per dataset. The histogram in this case displays the count of videos and the KDE puts a smoothed line over it to show the density of the occurrence. The aim of comparing the distributions of the two datasets is to exhibit how videos are shared between the categories.

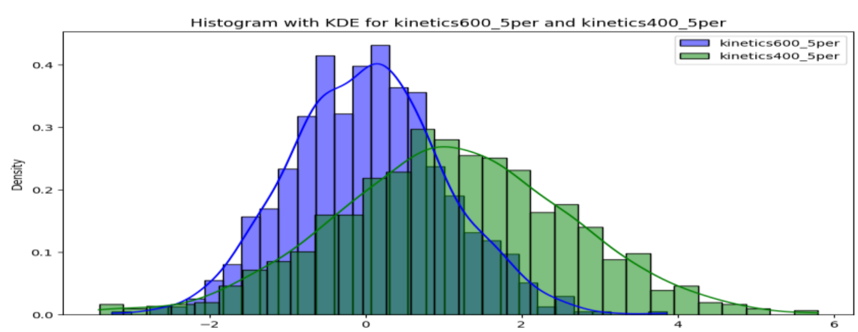

Figure 1: Histogram with KDE for kinetics600_5per and kinetics400_5per

This plot shows the number of videos in each of the classes in the whole dataset in Figure 2. It provides a Get LIABLE OF stereoscopic perspective of how the different videos are uploaded across the different classes of actions, making it easy to analyse the more dominant videos or those that are rarely featured. This is important for getting insights into potential imbalances in the data set that might impact the performance of the model.

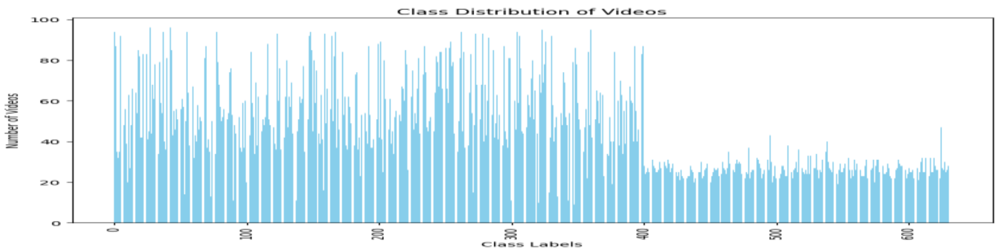

Figure 2: Class distribution of videos

Figure 3. demonstrates the typical frames per video for each of the varied classes. Investigating uniformity in video lengths along with looking at whether specific action classes possess longer, or shorter video durations has the potential to affect both model training and evaluation. It delivers an understanding of data consistency.

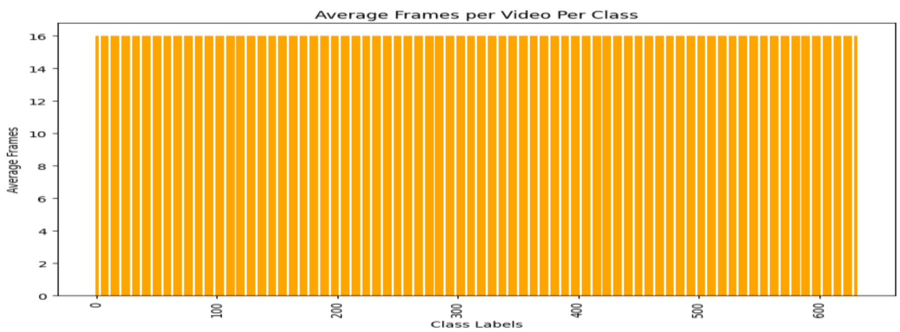

Figure 3: Average frames per video per class

The focus of Figure 4. Is on the classes that feature the largest number of recordings. Focusing on the 5 highest ranking action categories with a robust video presence can guide the decision on how to prioritize and teach the model to favour regular actions. This is important in keeping training efforts for frequently represented classes in balance.

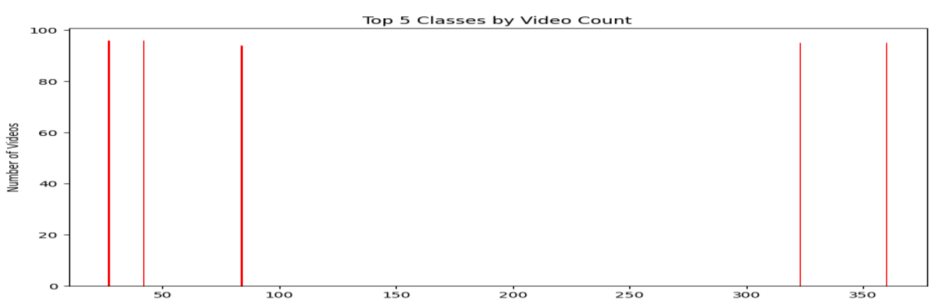

Figure 4: Top 5 classes by video count

This class distribution is in Figure 5. illustrates a detailed count of videos by class, distributed throughout all categories. This allows us to recognize those classes that might benefit from greater data collection or the application of oversampling techniques because of insufficient data. It also illustrates dataset balance, which is important for correct model training.

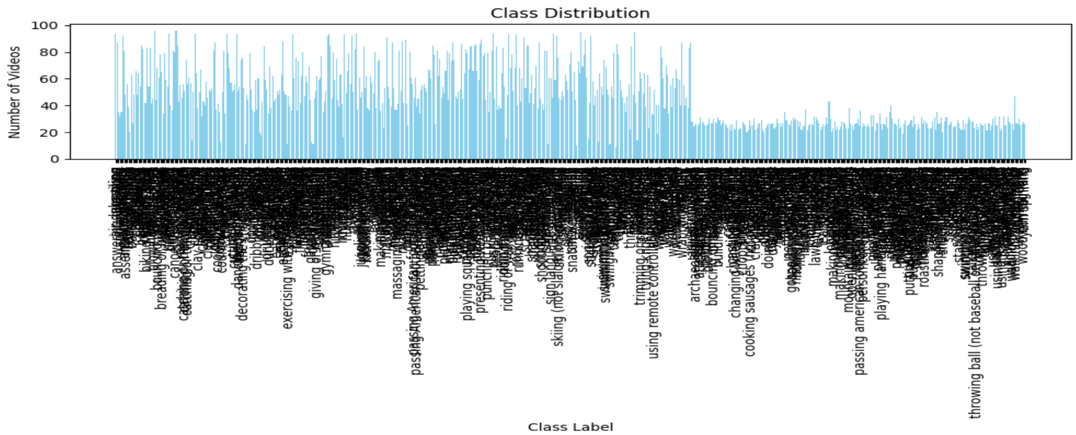

Figure 5: Class distribution

This pie chart visualizes, in Figure 6. The proportion of videos in different action categories, breaking down visually the contribution of each category to the entire dataset. It is useful in grasping data skew and in evaluating any rebalancing ideas during preprocessing.

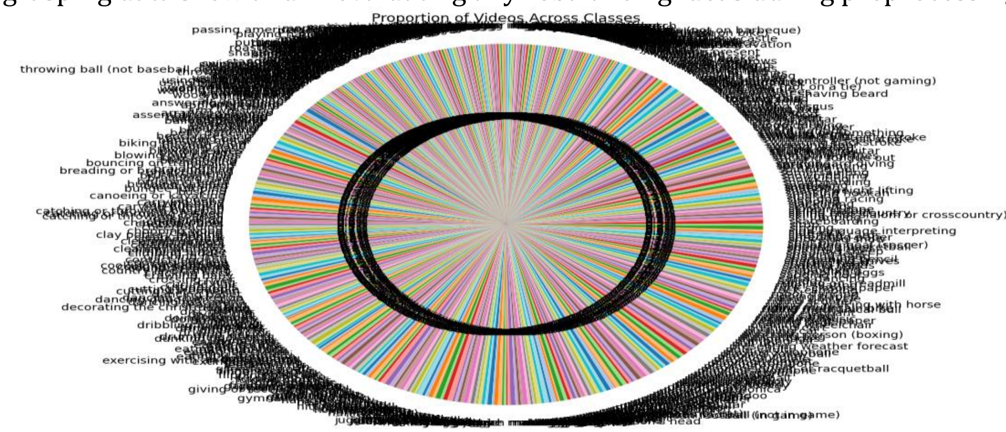

Figure 6: Portion of videos across classes

Figure 7. Depicts the number of videos stored in every directory, particularly concentrating on directories like kinetics600_5per and kinetics400_5per. Train action classes tend to have longer or shorter videos, which may influence the training and evaluation of models. It provides insights into data consistency.

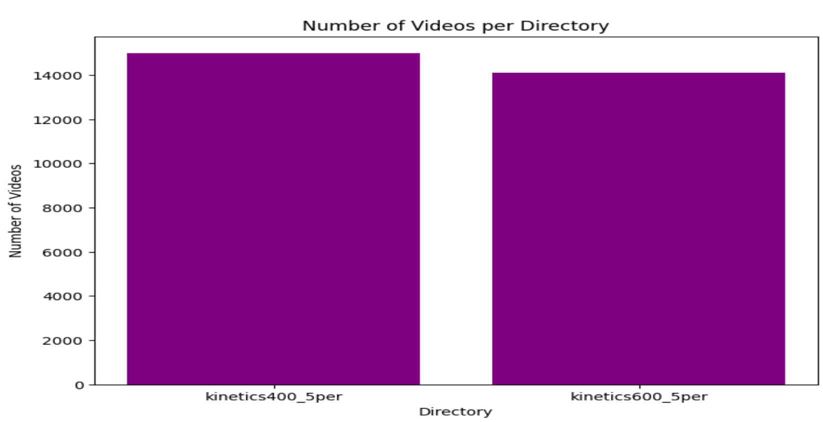

Figure 7: Number of videos per directory

This plot emphasizes the fraction of videos that have missing frames or unfinished data. The function of providing quality data, and missing frame detection plays a role in deciding whether to exclude or differently treat some videos during model training.

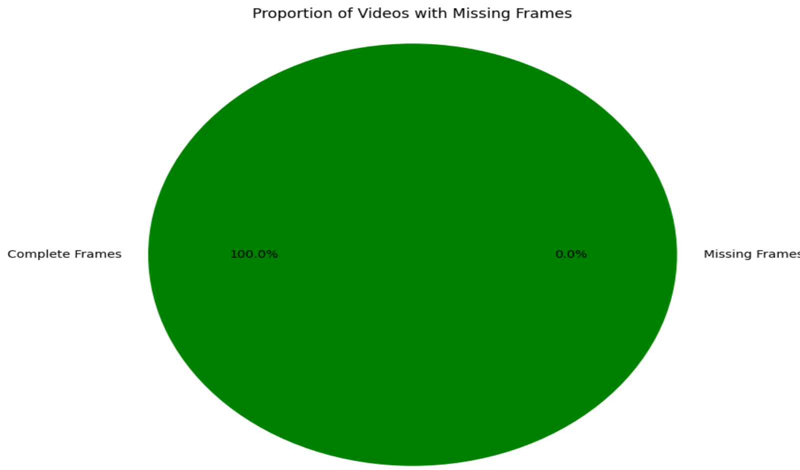

Figure 8: Proportion of videos with missing frames

The heatmap indicates the frequency level of each class in the data source. The vividness of the colours indicates the rate of videos for each class, making it easier to see class representation visually. This is an effective resource for promptly recognizing data disparities.

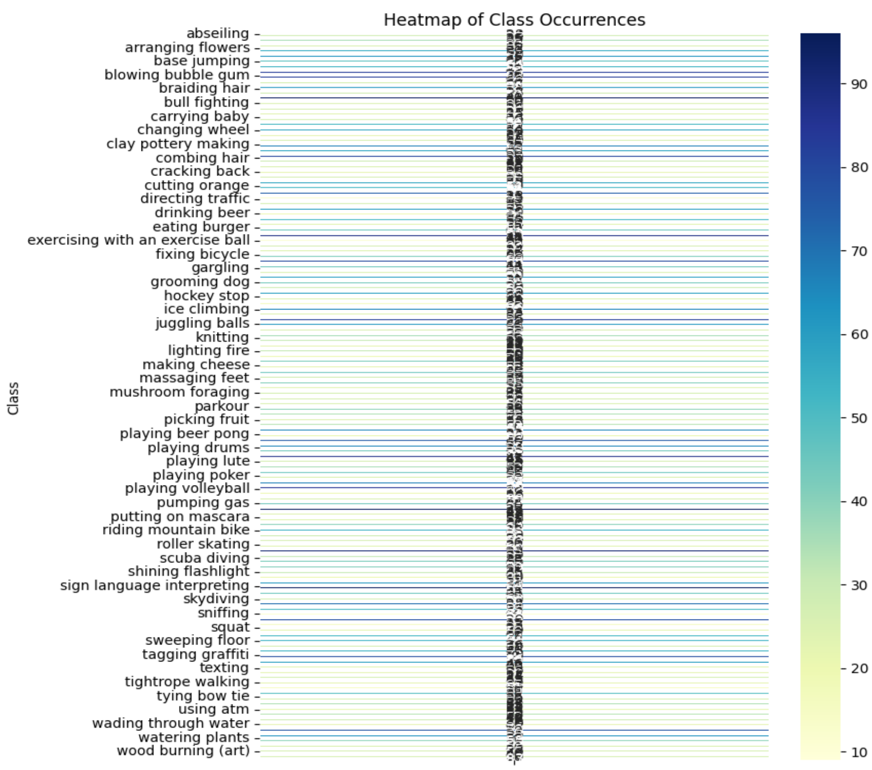

Figure 9: Heatmap of class occurrences

The Histogram is shown in Figure 10. gives the incidence of each class label, illustrating the frequency of observation for actions within the dataset. This reveals the difference in the quality of the dataset and supports the application of class balancing techniques, particularly reweighting or resampling, during the training phase. Figure 11 illustrates a facet grid that shows the division of frame counts for each category and represents the frequency of videos for each class, making it easier to visually grasp the class representation. This is an effective tool for quickly identifying data imbalances.

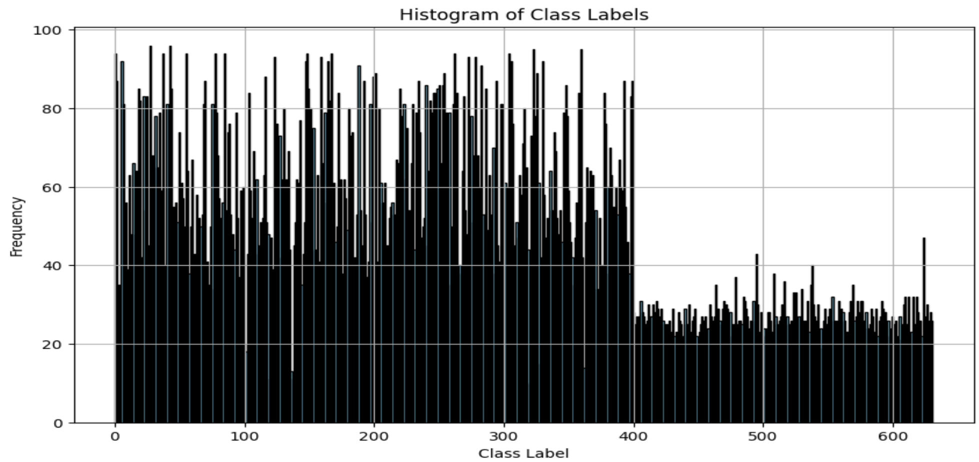

Figure 10: Histogram of class labels

Data preprocessing

The processing of data is important for getting video data ready for feature extraction and classification, as it makes the input format smoother and enhances model efficiency. Originally, processing each video yielded a fixed number of frames; in this instance, 16 frames were extracted from all videos to guarantee a faithful representation of the shifting content. In the wake of frame extraction, all frames were made uniformly 64x64 pixels. The resizing operation is necessary for providing uniform input dimensions in all videos, an essential factor for deep learning models that need fixed-size inputs [19]. Ultimately, labels were distributed according to the structure of the dataset's folders, where each folder correlates with a specific class or activity, making organization and identification of data for supervised learning tasks easier [20].

Table 1. shows the frequency of occurrences for the array of activities featured in the dataset. Every class illustrates an action that corresponds to its frequency of observation. The counts track incident numbers, disclosing information related to activity distribution. This data is significant in illuminating the breadth of specific classes that can affect both the training and performance of classification models. The information clarifies the most usual tasks and supports better resource assignment in machine learning initiatives.

Table 1: Count of occurrences for each class

Class	Count
Abseiling	**95**
Arranging flowers	**96**
Base jumping	**94**
Blowing bubble gum	**92**

Braiding hair	**90**
Bullfighting	**93**
Carrying baby	**94**
Changing wheel	**92**
Clay pottery making	**95**
Combing hair	**90**
Cracking back	**93**
Cutting orange	**94**
Directing traffic	**95**
Drinking beer	**92**
Eating burger	**93**
Exercising with an exercise ball	**91**
Fixing bicycle	**94**
Gargling	**92**
Grooming dog	**95**
Hockey stop	**93**
Ice climbing	**90**
Juggling balls	**96**
Knitting	**94**
Lighting fire	**92**
Making cheese	**91**
Massaging feet	**93**
Mushroom foraging	**95**
Parkour	**94**
Picking fruit	**93**
Playing beer pong	**91**

Playing drums	**92**
Playing the lute	**95**
Playing poker	**96**
Playing volleyball	**94**
Pumping gas	**91**
Putting on mascara	**93**
Riding mountain bike	**95**
Roller skating	**92**
Scuba diving	**94**
Shining flashlight	**91**
Sign language interpreting	**93**
Skydiving	**92**
Sniffing	**94**
Squat	**96**
Sweeping floor	**92**
Tagging graffiti	**93**
Texting	**94**
Tightrope walking	**92**
Tying bow tie	**95**
Using ATM	**93**
Wading through water	**94**
Watering plants	**92**
Wood burning (art)	**90**

Table 2 shows how the distribution of classes in the dataset corresponds to the number of videos related to each category index. There are a total of 632 classes, along with 29,086 videos recorded, giving an extensive view of the dataset's structure. This table supports the evaluation of the diversity and class balance within the dataset.

Table 2: Class distribution table

Class	Count
0	96
1	96
2	95
3	95
4	94
627	11
628	11
629	11
630	10
631	9
Total Classes	632
Total Videos	29086

In Table 3, we find the summary statistics related to the frame count of the videos, showing a total of 29,086 videos. The standard frame count remains 16, and there is no variation (standard deviation is 0), representing a continuous frame extraction process. This kind of uniformity is important for assuring steady input dimensions during video classification tasks.

Table 3: Frame count summary statistics

Statistic	Value
Count	29,086
Mean	16
Std Dev	0
Min	16
25%	16
50%	16
75%	16
Max	16

In Table 4, duration summary statistics confirm that the videos all share a consistent duration of close to 0.53 seconds. The consistency in length, free from standard deviation, stresses the managed character of the video sampling process. This stability provides support for the validity of duration calculations in later modelling attempts.

Table 4: Duration summary statistics (seconds)

Statistic	**Value**
Count	**29,086**
Mean	**0.533333**
Std Dev	**0.000000**
Min	**0.533333**
25%	**0.533333**
50%	**0.533333**
75%	**0.533333**
Max	**0.533333**

Table 5 illustrates the leading five classes with the greatest video quantities, organizing them by the number of occurrences present. The table discloses that classes 27 and 42 have the maximum number of videos, with 96 each, and class 323 follows with a close 95.

Table 5: Top 5 classes with the most videos

Rank	**Class**	**Video Count**
1	**27**	**96**
2	**42**	**96**
3	**323**	**95**
4	**360**	**95**
5	**84**	**94**

Modelling and classification

A Random Forest Classifier was used in this study to study the dataset, with specific attention given to the precise classification of dance activities along with the identification of their biomechanical aspects. Understanding the performance of the model against non-deep learning alternatives was possible because of the Random Forest approach, which revealed its robustness and efficiency. The dataset separation into training and validation parts was done with a ratio of 80 to 20 to properly train the model and support meaningful evaluation. We used standard classification metrics, like accuracy, precision, recall, and F1-score to evaluate every class, which enabled a complete evaluation of the model's competence in differentiating between assorted dance movements, therefore deepening our understanding of sports dance dynamics [21, 22].

Findings from Modelling

In elite sports dance, artistry is just a small part; the real story is the detailed relationship between movement, rhythm, and biomechanics that calls for skill and accuracy. Understanding the detailed mechanisms of biomechanics in between several dance movements is important for optimizing performance, lowering injury risk, and progressing training approaches. Our research employed an extensive machine learning method, notably a Random Forest Classifier, to analyse the Kinetics 600 dataset and uncover insights into classifying a range of dance activities. Our analysis findings demonstrate important patterns and challenges, providing a rich understanding of the biomechanics that characterize top sports dance.

Insights into performance metrics

According to our classification analysis results, we saw an overall accuracy of 0.76, demonstrating that 76% of the videos received their correct classification into the specified activities. The macro average precision calculated was 0.65, with recall and F1-score reported at 0.59 and 0.60, respectively. These markers illustrate the model's capability to classify and isolate differing activities; they also uncover challenges, with several categories showing lower performance figures.

Accuracy: A successful outcome of 76% accuracy shows that the model has effectively learned to distinguish a majority of the activities present in the dataset. It does illustrate a chance for progress, especially in fine-tuning the model to better identify the rare dance movements.

Precision and recall: The macro average precision of 0.65 reveals that, commonly, the model successfully determined 65% of the cases it projected as belonging to each class. Still, the recall report shows that the model successfully detected only 59% of each class's real instances. This variation suggests that although the model frequently succeeds in predicting correctly for specific classifications, it has trouble with the extensive detection of cases linked to certain activities. Such insights are important in realizing the constraints of the model and laying the groundwork for future improvements.

Class performance: During our analysis of the individual class performances, we observed that precision and recall varied across several activities. As a case in point, while several classes showed precision over 0.80, indicative of solid performance, others, particularly those with scant support instances, experienced poor results, with precision lowering to 0.50 and recall slipping as low as 0.25. This points out a standard problem in classification assignments called class imbalance, in which a few activities lack adequate data representation, impeding the model's capability to effectively learn their features.

Table 6. Presents the performance of the Random Forest classifier in recognizing a wide range of activities from the Kinetics 600 dataset. The model successfully classified most activities with an accuracy of 0.76, but the variability among classes shows up in a macro average precision of 0.65 and recall of 0.59. A score of 0.60 on the F1 indicates the challenges in categorizing specific complex or underrepresented activities, which indicates a need for greater refinement in the documentation of the complexities of specific movements.

Table 6: Classification metrics summary

Metric	Value
Accuracy	0.76
Macro Average Precision	0.65
Macro Average Recall	0.59
Macro Average F1-Score	0.60

Table 7. Evaluates the broad performance of the Random Forest classifier considering the activity distribution of the Kinetics 600 dataset. With a weighted average precision of 0.74, the model tends to produce correct predictions for the more commonly observed activities. The model shows its capability to correctly identify the majority of activity instances, especially those cases that are better represented, through a weighted average recall of 0.76. The weighted average F1-score at 0.74 reinforces balanced success in the recognition of main activities and compensating for the class imbalance in the dataset. The model shows strong performance in recognizing popular activities but fails to accurately differentiate less common or rarely visible movements.

Table 7: Weighted average metrics

Metric	Value
Weighted Average Precision	0.74
Weighted Average Recall	0.76
Weighted Average F1-Score	0.74

The Kinetics 600 dataset presents the classification performance of the Random Forest model as shown in Figure 11. The graphic shows important evaluation parameters, which include accuracy, precision, recall, and F1-score, related to 632 classes. An overall accuracy of 76% was achieved, along with macro average precision and recall values of 0.65 and 0.59, respectively, showing that the model can effectively distinguish activities, even though there are remaining difficulties with underrepresented classes. The figure illustrates a complete examination of how effectively the model recognized the array of dance movements in the dataset. Table 6. shows how well the Random Forest classifier fares in recognizing a complete assortment of activities from the Kinetics 600 dataset represents key evaluation metrics, including accuracy, precision, recall, and F1-score, across 632 classes. The overall accuracy achieved was 76%, with macro average precision and recall values of 0.65 and 0.59, respectively, highlighting the model's ability to distinguish between activities, though challenges remain with underrepresented classes. The figure provides a comprehensive view of how well the model performed in recognizing the diverse dance movements present in the dataset.

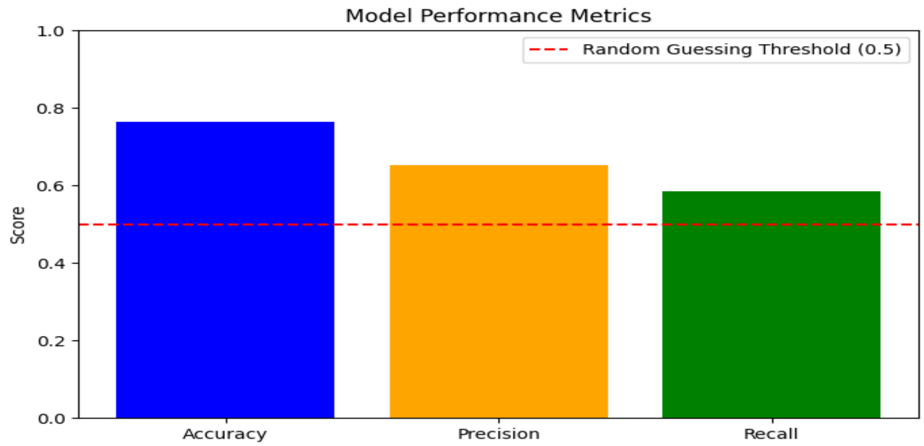

Figure 11: Model performance metrics

Linking results to biomechanics in dance

Derived from the Kinetics 600 dataset, the classification results present useful knowledge about the biomechanics of top-tier sports dance and directly link to the performance and understanding of diverse movements in practice. To analyse their biomechanical foundations, dance movement classification is indispensable to coaches, athletes, and researchers, who can then identify and refine specific techniques for both performance and injury reduction. The right categorization of movements that need a combination of finesse and equilibrium (including pirouettes and jumps) results in better training protocols and lessened injury risk through the optimization of biomechanics [23].

The poorer performance metrics of certain dance movements may underscore unique biomechanical qualities that call for further attention. This finding indicates that some activities exhibit movement patterns that are hard to capture by machine learning models, recognized as a sign of intricate underlying movement dynamics [24]. In sports science studies, researchers must understand these biomechanical signatures to improve movement methods and keep athletes safe while they perform. Research has shown that biomechanical analysis is important for preventing injuries related to dance by revealing imbalances in technique [25].

When a particular movement is repeatedly misclassified, it indicates that the data set is missing representation, or there may be kinematic attributes of the movement that are not fully represented. These results suggest a critical need for more thorough biomechanical analyses, enabling the identification of central movement components and supporting improvements in training methods [26]. The studies suggest that wearable technology can work with machine learning models, allowing for the real-time acquisition of dance movement information that likely improves classification accuracy and expands biomechanical insights [27].

DISCUSSION AND CONCLUSION

Overview of findings

Previous studies about dance biomechanics have typically relied on traditional motion capture systems, concentrating primarily on contemporary or classical dance forms. Comparing the results of this study with those of [16] on dance biomechanics in elite sports, significant similarities and differences emerged. Both studies used machine learning approaches to classify complex actions, emphasizing the growing significance of modern analytical techniques in recognizing human actions. Although our study achieved a total of 76% accuracy using the Kinetics 600 dataset focusing on a random forest algorithm, [16] Using a dual-stream CNN architecture on a multi-view outdoor dataset of action recognition, the reported accuracy was slightly lower at 74%. This correlation in accuracy illustrates both methods' robustness in analysing biomechanical and movement-related data. However, an important difference lies within the data nature and the task specificity. Our study explores the biomechanical properties of different dance movements, exposing gaps in the ability of current models to capture nuances, whereas [16] Focuses on common human behaviours in a variety of contexts. This comparison demonstrates that although both studies have made significant contributions to their respective fields, our work requires further refinement of the biomechanical analysis to improve training methods and movement differentiation for movement dance. Figure 12 shows the performance comparison of the proposed study with previous study

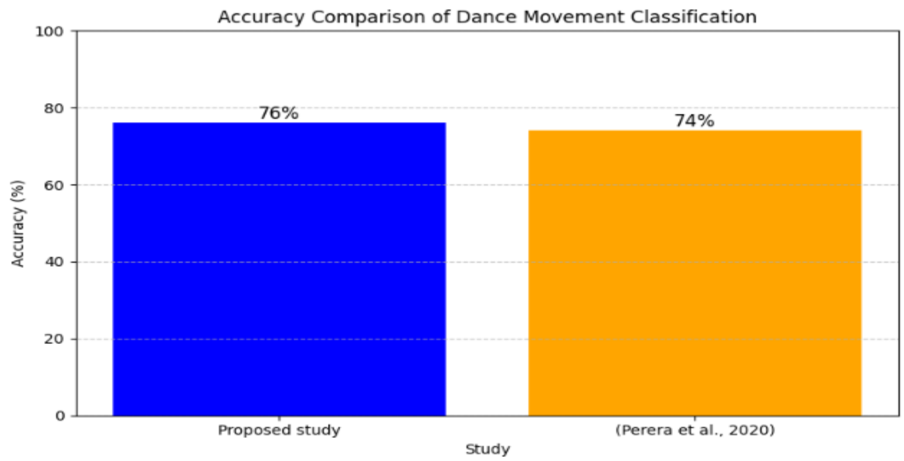

Figure 12: Model comparison with previous study

Implications

The results of this study highlight the significance of machine learning algorithms integrating in understanding dance biomechanics in elite sports. The random forest successful application highlights how state-of-the-art computational techniques can efficiently analyse and classify complex movements in the dance domain. Athletes also benefit highly from the insights. By leveraging the ability of the model to effectively classify activities, dancers can create a personalized training system. This personal approach not only promotes excellent achievement but also leads to a higher awareness of one's physical abilities and limitations. With this knowledge, dancers can create more informed judgments regarding their training, guiding them to better results in practice and achievement. In a deep context, this study contributes to the growing literature on the biomechanics and exercise science intersection. This study highlights the role of ML as a valuable mechanism for analysing complex sports data, advocating for advanced computational techniques integration into sports implementation analysis. The dance movement nuances illustrated in this study demonstrate the complex relationship between athletic excellence and biomechanics. This wisdom is important for dancers and coaches because it provides an approach for improving training models and injury avoidance strategies. By accurately understanding and classifying dance movements, stakeholders can develop training systems that improve performance and decrease the risk of injury, thereby enhancing comprehensive dance outcomes.

LIMITATIONS

Although this study provides valuable insights into elite sport dance, it is crucial to acknowledge some limitations that may affect the robustness of the results. One notable difficulty is the imbalance classes in the Kinetics 600 dataset. In particular, some activities are considerably underrepresented, which may degrade model performance and reduce the accuracy of classifying these small common activities. This imbalance class suggests a challenge for ML as models prefer the majority class favour, resulting in generalizability and the potential bias opposed to minority classes. Data augmentation techniques are ignored which can be essential in executing a more stable dataset. Another limitation is the choice of RF used in this study. Although RF is appreciated for its robustness and effectiveness in managing complex datasets, it may not completely capture the complexity of the movement dynamics involved in dance moves. The stochastic nature of this algorithm sometimes oversimplifies the correlation between the target and the feature classes, potentially unknown subtle but important nuances that provide accurate classification. Thus, other techniques which are especially appropriate for interpreting and processing high-dimensional data can be taken. Furthermore, reliance on only the dataset may restrict the validity of the results. While comprehensive, the Kinetics 600 dataset cannot cover all dance moves performed in different contexts and styles. The findings will be validated using a diverse dataset which includes various dance genres, participant demographics, performance conditions, and participant populations. Finally, although this research effectively establishes the ML potential in examining dance movements, interpretation of the results is naturally limited through the ability of the model to provide relevant insights. While ML can classify moves, it doesn't naturally explain why certain moves are performed a specific way, or how specific dancers might perform them differently.

FUTURE WORK

Based on the results of this study, several encouraging avenues for future study are recommended that may further improve the dance biomechanics understanding in elite sports.

One of the main suggestions is to increase the dataset to include a wider range of dance moves, genres, and styles. By boosting the underrepresented categories representation, researchers can improve the accuracy and robustness of ML models. A more extensive dataset will not just improve classification achievement but also give wisdom into the complexities and nuances of different dance forms, permitting a movement dynamics analysis. Additionally, expanding the dataset, and incorporating dancers' sensor data during practice also provides important opportunities for more research. Incorporating wearable sensors or motion capture methods can give real-time biomechanical feedback to capture complex dance movements. This real-time data can facilitate an understanding of more dynamic than how dancers adjust their movements in response to feedback and sustainable conditions, thereby enhancing the ML application and analysis in this field. Additionally, this integration allows for personalized training plans based on the individual needs of dancers, improving their achievement while reducing the risk of injury. Future research should be intended to incorporate qualitative analyses, like dancer feedback or expert reviews, to correlate quantitative results and provide a better performance dynamics understanding involved in dance sports.

Another area worth exploring includes the hybrid models that merge traditional ML techniques with advanced DL methods. While traditional classifiers such as RF are useful, harnessing the power of DL can yield more important insights into dance biomechanics. Hybrid models which combine the interpretation of traditional techniques with the recognition pattern capabilities of DL can provide more extensive complex movements. For instance, combining RF with CNN (convolutional neural networks) or RNN (recurrent neural network) can facilitate in-depth analysis of spatial and temporal patterns of dance movements and the development of advanced training techniques and injury avoidance strategies.

Additionally, more studies should examine longitudinal works that track the progress of dancers over time, evaluating how parameters of biomechanical change with experience and training. These works can give valuable insights into the effectiveness of special training regimens by highlighting the changes of biomechanical associated with enhanced performance.

Furthermore, exploring aspects of psychological dance performance, like the influence of psychological states on movement implementation, can provide a comprehensive view of athletic greatness in dance sports.

Finally, an interdisciplinary synergy that integrates insights from areas like kinesiology, coaching science, and sports psychology can greatly improve the research findings' applicability. By cultivating interdisciplinary partnerships, researchers can make comprehensive training techniques that combine biomechanical analysis through athlete-centred training strategies.

CONCLUSION

In conclusion, this research contributes to the biomechanics understanding of elite sports dance by using the Kinetics 600 dataset and applying advanced ML classification methods. The results highlight the ability of computational techniques to effectively examine and interpret complex personal movements, thereby giving valuable insights into the biomechanics behind different dance movements. Reaching an accuracy of 76% verifies that ML models, specifically the RF classifier used in this study, can successfully differentiate between various dance activities. This achievement not only identifies the ML efficiency in this unique field but also underscores the significance of ongoing work to improve model training methods and enhance data representation.

This study has significant implications for the dance community, including coaches, athletes, and sports scientists. Understanding the biomechanics of dance movements enables the development of targeted training programs that enhance performance while minimizing injury risk. The ability to analyse and classify different movement patterns paves the way for personalized training regimens tailored to each dancer's specific needs, potentially leading to improved athletic outcomes. However, it's crucial to acknowledge the study's limitations, such as dataset class imbalance and the complexity of motion dynamics that may not be fully captured by the chosen classification model. Addressing these limitations in future research will be essential for advancing the field and achieving higher accuracy in movement classification. Furthermore, integrating this biomechanical approach with other aspects of dance performance, such as artistic expression and musicality, could provide a more comprehensive framework for dance training and assessment.

REFERENCES

Fotaki, A., et al., *The science of biomechanics can promote dancers' injury prevention strategies.* Physical Therapy Reviews, 2021. **26**(2): p. 94-101.

Krasnow, D., et al., *Biomechanical research in dance: a literature review.* Medical problems of performing artists, 2011. **26**(1): p. 3-23.

Burns, G.T., K.M. Kozloff, and R.F. Zernicke, *Biomechanics of elite performers: Economy and efficiency of movement.* Kinesiology Review, 2020. **9**(1): p. 21-30.

Rice, P.E., R.D. Gurchiek, and J.M. McBride, *Physiological and biomechanical responses to an acute bout of high kicking in dancers.* The Journal of Strength & Conditioning Research, 2018. **32**(10): p. 2954-2961.

Mattiussi, A., et al., *Jumping in ballet: a systematic review of kinetic and kinematic parameters.* Medical Problems of Performing Artists, 2021. **36**(2): p. 108-128.

Teikari, P. and A. Pietrusz, *Precision strength training: Data-driven artificial intelligence approach to strength and conditioning.* 2021.

Mattiussi, A.M., *Injury, Strength, and Jumping in Professional Ballet*. 2024, St Mary's University.

Cantergi, D., L.R. Moraes, and J.F. Loss, *Applications of Biomechanics Analysis in Dance*, in *Scientific Perspectives and Emerging Developments in Dance and the Performing Arts*. 2021, IGI Global. p. 25-44.

Yeadon, M. and M. Pain, *Fifty years of performance-related sports biomechanics research.* Journal of Biomechanics, 2023. **155**: p. 111666.

Glazier, P.S. and S. Mehdizadeh, *Challenging conventional paradigms in applied sports biomechanics research.* Sports Medicine, 2019. **49**(2): p. 171-176.

Dorosh, G., et al., *Biomechanical Analysis of Sports Dance.* 2021.

Premelč, J., *TIME MOTION AND PERFORMANCE ANALYSIS IN TANGO DANCE.* Kinesiologia Slovenica, 2022. **28**(1).

Wu, F., et al., *A survey on video action recognition in sports: Datasets, methods and applications.* IEEE Transactions on Multimedia, 2022. **25**: p. 7943-7966.

Host, K. and M. Ivašić-Kos, *An overview of Human Action Recognition in sports based on Computer Vision.* Heliyon, 2022. **8**(6).

Li, Q., et al., *VideoBadminton: A Video Dataset for Badminton Action Recognition.* arXiv preprint arXiv:2403.12385, 2024.

Perera, A.G., et al., *A multiviewpoint outdoor dataset for human action recognition.* IEEE Transactions on Human-Machine Systems, 2020. **50**(5): p. 405-413.

Evola, V. and J. Skubisz, *Coordinated collaboration and nonverbal social interactions: A formal and functional analysis of gaze, gestures, and other body movements in a contemporary dance improvisation performance.* Journal of Nonverbal Behavior, 2019. **43**(4): p. 451-479.

Kay, W., et al., *The kinetics human action video dataset.* arXiv preprint arXiv:1705.06950, 2017.

Badrinarayanan, V., A. Kendall, and R. Cipolla, *Segnet: A deep convolutional encoder-decoder architecture for image segmentation.* IEEE transactions on pattern analysis and machine intelligence, 2017. **39**(12): p. 2481-2495.

Karpathy, A., et al. *Large-scale video classification with convolutional neural networks*. in *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*. 2014.

He, K., et al. *Deep residual learning for image recognition*. in *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.

Sokolova, M. and G. Lapalme, *A systematic analysis of performance measures for classification tasks.* Information processing & management, 2009. **45**(4): p. 427-437.

Hughes, M., I.M. Franks, and H. Dancs, *Essentials of performance analysis in sport.* 2015.

Gurchiek, R.D., N. Cheney, and R.S. McGinnis, *Estimating biomechanical time-series with wearable sensors: A systematic review of machine learning techniques.* Sensors, 2019. **19**(23): p. 5227.

Angioi, M., et al., *Fitness in contemporary dance: a systematic review.* International journal of sports medicine, 2009. **30**(07): p. 475-484.

Willwacher, S. and G. Weir, *The future of footwear biomechanics research.* Footwear Science, 2023. **15**(2): p. 145-154.

Liu, L. and X. Zhang, *A focused review on the flexible wearable sensors for sports: From kinematics to physiologies.* Micromachines, 2022. **13**(8): p. 1356.

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