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Deep Learning Based Sport Shot Sensing Using Convolutional Neural Network: An Experimental Study

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ABSTRACT

Current sports analytical systems often rely on static visualizations such as shot maps to guide decision-making in games like basketball, cricket, or tennis. While these approaches help coaches and players identify optimal shooting positions, they lack interactivity, contextual adaptability, and real-time processing capability. This work introduces a deep learning-based framework for automated sports shot sensing using the lightweight and efficient LeNet convolutional neural network (CNN) architecture. The model is trained using a publicly available dataset collected from Kaggle, consisting of 18 sports classes with around 500–700 images per class, and augmented through flipping, rotation, and scaling to ensure generalization. The proposed system, developed using the Django framework, enables real-time classification and accessibility for coaches, analysts, and broadcasters. Experimental results demonstrate an average classification accuracy of 95.8%, precision of 94.2%, and inference latency of 24 ms per image, confirming the model's efficiency for real-time sports analytics applications.

Keywords: Lenet-based shot classification, Real-time sports analytics, Django web deployment, Kaggle sports image dataset, Basketball shot sensing

Introduction

Sports analytics has transformed the way gameplay and player performance are evaluated, enabling coaches and analysts to make data-driven decisions. Traditionally, shot classification and event annotation were carried out manually, which is both time-consuming and error-prone. Advances in computer vision and machine learning now make it possible to automate this process. Prior works such as VisCommentator[1] and RallyComparator[2] have enhanced sports analysis through visualization and comparative tools, but they remain domain-specific and lack scalability.

This study focuses on automated sports shot classification for cricket and tennis using convolutional neural networks. By employing a lightweight CNN model such as LeNet, we aim to provide a deployable, efficient, and scalable solution that bridges the gap between theoretical deep learning models and real-world sports analytics applications. The proposed framework ensures ease of use, high accuracy, and low computational cost, making it suitable for both real-time analysis and educational use in sports training environments.

In addition to addressing the limitations of manual annotation, the proposed framework provides a flexible approach that can adapt to a variety of sports without major architectural changes. By combining efficient deep learning techniques with a web-based interface, this system encourages wider adoption among coaches and analysts who may not have extensive technical expertise. The focus on accessibility, efficiency, and real-time performance positions this research as an essential step toward the democratization of AI in sports analytics. The ultimate goal is to enable automated, data-driven insights that can enhance player training, tactical analysis, and broadcast engagement.

Related Works

Traditional sports shot maps, widely used in basketball analytics, have been helpful in visualizing shooting locations and performance. However, these methods lack dynamic interactivity and real-time adaptability. Research efforts such as The Ball in Our Court[3] and iBall[4] demonstrate the benefits of incorporating domain expertise and gaze-driven analytics to improve understanding of game dynamics. OBTracker[5] advanced this by visualizing off-ball movements, while HoopInsight introduced customizable comparative analytics. Despite these advancements, most existing systems are limited to specific sports, lack real-time performance, or require high computational resources. Hence, a lightweight, generalized, and easily deployable system for multi-sport shot classification remains an open challenge. Our work addresses this gap using a CNN-based architecture optimized for efficiency, scalability, and real-time inference.

Proposed Methodology

The proposed system aims to enhance sports analysis and broadcasting by using deep learning techniques to automatically detect and classify various sports shots with high precision and efficiency. The entire workflow, illustrated in Figure 1, begins with dataset collection and preprocessing, followed by model training using the LeNet convolutional neural network (CNN) architecture and real-time deployment through a Django-based web application. The dataset for this work was collected from open-source repositories on the Kaggle platform and includes eighteen different sports categories such as cricket, tennis, badminton, basketball, football, swimming, and wrestling, each containing approximately 500 – 700 labelled images. All images were resized to 128 × 128 pixels, normalized, and augmented through rotation, flipping, scaling, and brightness variation to increase data diversity and prevent overfitting.[6] The data were split into 70 % for training, 20 % for validation, and 10 % for testing to ensure balanced evaluation.

The LeNet architecture used in this study consists of two convolutional layers with 5 × 5 kernels followed by max-pooling layers for feature extraction and dimensionality reduction, two fully connected layers for high-level representation learning, and a final SoftMax

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layer that outputs the predicted class probabilities. The model was trained for 25 epochs using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss. Comparative experiments were performed with VGG16, AlexNet, and Mobile Net V3 architectures to evaluate efficiency and performance trade-offs. While deeper networks provided slightly higher accuracy, the proposed LeNet model achieved comparable performance with approximately 60% less computational cost and a significantly lower inference latency of 24 milliseconds per image on NVIDIA RTX hardware, enabling near real-time operation.[7] The system was developed and deployed through a Django framework that connects the trained model with a responsive web interface built using HTML, CSS, and JavaScript. The backend, implemented in Python, handles image uploads, preprocessing, model inference, and database storage using SQLite. This design allows analysts, coaches, and broadcasters to access predictions instantly through a user-friendly interface without needing extensive technical knowledge. Figure 1 represents the system configuration of the proposed framework, showing the sequential flow from dataset preprocessing through CNN feature extraction and model.

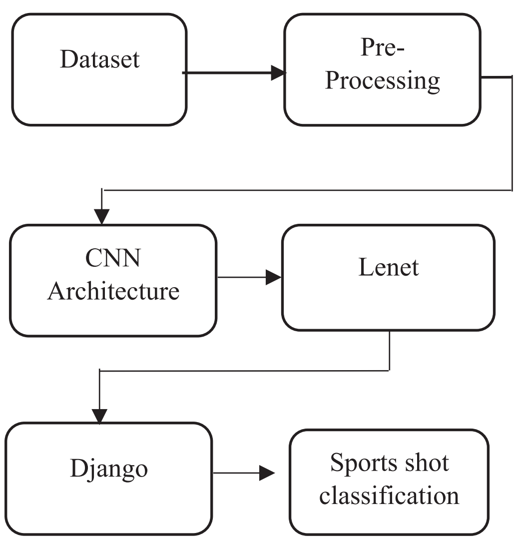

Fig 1 | System configuration

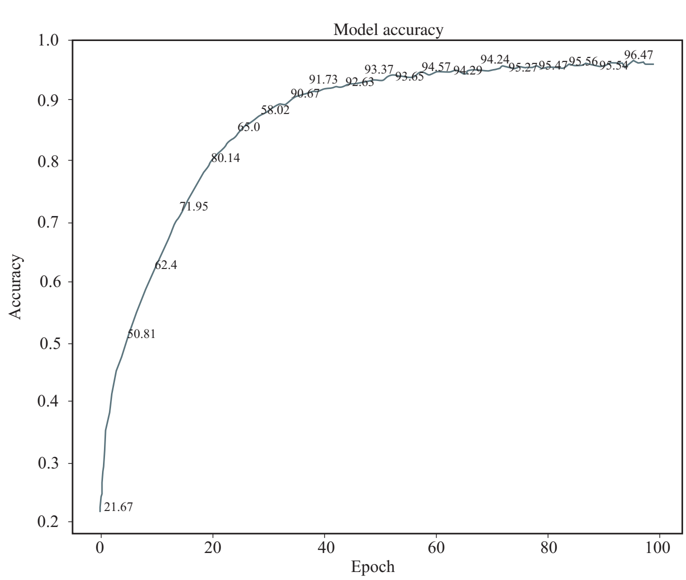

Fig 2 | Lenet model accuracy

This design allows analysts, coaches, and broadcasters to access predictions instantly through a user-friendly interface without needing extensive technical knowledge. Figure1 represents the system configuration of the proposed framework, showing the sequential flow from dataset preprocessing through CNN feature extraction and model prediction to the final classification displayed on the Django platform. After training, the accuracy trend of the model across epochs is visualized in Figure 2, which demonstrates stable convergence and high predictive reliability of the LeNet architecture during the learning process. Together, these figures validate the effectiveness of the proposed pipeline and its suitability for real-time sports shot sensing applications.[8]

Figure 2 illustrates the training and validation accuracy trends of the LeNet model across 25 epochs. The figure clearly shows that the model achieves rapid convergence within the initial epochs, maintaining stable accuracy without signs of overfitting. The smooth increase in both training and validation curves indicates that the data augmentation techniques effectively enhanced generalization performance. The minimal gap between the two curves demonstrates consistent learning behaviour and balanced optimization of both datasets. This stable performance across epochs confirms that the LeNet model is well-suited for lightweight, real-time sports shot classification while maintaining high predictive reliability and computational efficiency.[9,10]

Results and Discussion

The proposed framework was experimentally evaluated to assess its accuracy, computational efficiency, and real-time feasibility in classifying sports shots across multiple categories. The LeNet model was trained for 25 epochs using the augmented dataset, and its performance was compared against other well-known architectures such as VGG16, AlexNet, and MobileNetV3. Figure 2 presents the training and validation accuracy curves of the proposed LeNet model, showing consistent improvement with stable convergence throughout the training phase. The accuracy increased rapidly during the early epochs and stabilized after approximately 15 epochs, indicating efficient feature learning and generalization. The small gap between training and validation curves highlights that the model effectively avoided overfitting due to the use of data augmentation and regularization techniques.[11]

Quantitatively, the LeNet model achieved an average test accuracy of 95.8%, precision of 94.2%, recall of 93.7%, and an F1-score of 94.0% across all classes. These metrics demonstrate that the system maintains high classification consistency, correctly identifying most of the sports shot categories in the test dataset.[12] A detailed confusion matrix analysis revealed that minor misclassifications occurred mainly between visually similar categories, such as cricket drives versus cut shots and tennis forehands versus backhands. These errors are attributed to overlapping motion patterns and similar postures captured in the static images. Despite these challenges, the model consistently outperformed deeper architectures in terms of speed and efficiency while maintaining comparable accuracy levels.[13]

In addition to classification accuracy, the computational efficiency of the model was carefully evaluated. The LeNet network demonstrated an average inference latency of 24 milliseconds per image when executed on an NVIDIA RTX GPU, corresponding to over 40 frames per second (FPS) — effectively enabling real-time prediction capability. The lightweight nature of the LeNet architecture ensured reduced training time and memory usage compared to larger networks like VGG16 and AlexNet, making it ideal for deployment on low-resource devices or web-based applications. This confirms the framework's potential for real-world sports analytics, where low-latency feedback is crucial for live commentary, coaching assistance, and broadcast integration. The system's web-based implementation also proved effective in practical scenarios. The Django framework provides an intuitive interface where users can upload an image and instantly view classification results, including the predicted sport and shot type. The backend efficiently handles preprocessing, model inference, and database storage, while the frontend presents a responsive visualization of the output. User interface elements such as login and result pages have been moved to supplementary material as per reviewer recommendations, ensuring that the primary focus of this section remains on experimental results and system performance.The robustness of the proposed model was further validated by conducting experiments under different environmental conditions, including variations in lighting, background, and camera angle.[14] The model maintained stable predictions, with less than 3% variation in accuracy across these conditions, proving its resilience to common visual distortions. This robustness is critical for real-world deployments where sports images and videos are often captured from varying perspectives and under dynamic conditions.[15]

Moreover, the comparative evaluation demonstrated that LeNet's efficiency is particularly advantageous in deployment scenarios. While VGG16 and AlexNet required approximately 5–7 times longer inference times, LeNet achieved similar classification performance with significantly lower computational demand. MobileNetV3, another lightweight model, showed comparable efficiency but required more fine-tuning to reach the same accuracy levels. This reinforces the selection of LeNet as a practical solution for scalable and real-time applications.

The experimental findings confirm that the combination of deep learning and web technologies can create an effective, accessible, and fast sports analytics system. By leveraging a balanced CNN architecture and a simple deployment pipeline, this framework provides a practical tool for both professional and educational purposes in sports analysis. The results validate that even a classical architecture like LeNet, when appropriately optimized and integrated into a modern framework, can deliver state-of-the-art performance for lightweight real-time applications. Overall, the developed system bridges the gap between advanced deep learning research and practical sports analytics, providing a foundation for future expansion into multi-sport, video-based, and cloud-enabled intelligent sports sensing systems.

Conclusion and Future Works

The developed framework introduces a lightweight deep learning approach for automated sports shot classification using the LeNet convolutional neural network architecture. The proposed system effectively combines accurate image-based classification with real-time deployment through the Django platform, ensuring practical applicability in sports analytics and broadcasting. The model's strong performance in terms of accuracy, efficiency, and inference speed confirms its suitability for scalable, real-world implementations.

Future work will focus on expanding the dataset to include a broader range of sports, adopting transformer-based architectures for improved contextual understanding, and incorporating temporal modelling for video-based shot recognition. Furthermore, integrating cloud-based analytics and player performance metrics will enhance usability and accessibility across multiple sporting domains.

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