Salud, Ciencia y Tecnología - Serie de Conferencias. 2024; 3:.760
doi: 10.56294/sctconf2024.760

ORIGINAL

Badminton Service Foul System Based on Machine Vision

Badminton Service Foul System Basado en Visión Artificial

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Cite as: Chen Z, Caluyo F, Louise de Ocampo A, Hernandez R, Sarmiento J. Badminton Service Foul System based on machine vision. Salud, Ciencia y Tecnología - Serie de Conferencias. 2024; 3:.760. https://doi.org/10.56294/sctconf2024.760

Submitted: 02-01-2024 **Revised:** 21-05-2024 **Accepted:** 06-09-2024 **Published:** 07-09-2024

Editor: Dr. William Castillo-González

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ABSTRACT

Introduction: in today's sports activity landscape, the identity of fouls and misguided moves in badminton poses extensive challenges. A badminton carrier foul takes place when a player fails to stick to the guidelines in the course of a serve. Common fouls such as improper position, foot placement and racket position.
Objetive: the purpose of this study is to improve an advanced machine version system using Archerfish looking Optimization-driven intelligent ResNet50 (AHO-IResNet50) to enhance the accuracy of service foul identification in badminton, thereby improving match score analysis and decision-making for the Badminton practices.
Method: the dataset were obtained that incorporates numerous images capturing various phases of badminton matches, with racket positions and player movements during service, to train the proposed model. A discrete Wavelet rework (DWT) algorithm is utilized to extract the huge features. The proposed method includes an AHO algorithm to fine-tune the IResNet50 model for more desirable badminton service foul identification. This proposed approach leverages the adaptability of Archerfish hunting strategies to optimize IResNet50's parameters, enhancing accuracy and reducing errors in badminton foul recognition.
Results: the suggested recognition model is applied in a Python software program. During the result analysis phase, we evaluated the model's efficacy across diverse parameters along with accuracy (94,7 %), precision (86,7 %), recall (84,9 %), and specificity (93,5 %). We additionally conduct comparative analyses with existing methodologies to examine the effectiveness of our suggested classification.
Conclusions: the acquired findings show the efficacy and superiority of the proposed framework, significantly lowering errors and improving the accuracy of foul identification.

Keywords: Badminton Service; Foul Identification; Archerfish Hunting Optimization-Driven Intelligent ResNet50 (AHO-IResNet50); Machine Vision.

RESUMEN

Introducción: en el panorama actual de la actividad deportiva, la identidad de las faltas y los movimientos equivocados en el bádminton plantea grandes retos. Una falta de portador de bádminton tiene lugar cuando un jugador no se adhia A las directrices en el curso de un servicio. Faltas comunes como posición incorrecta, colocación del pie y posición de raqueta.
Objetivo: el propósito de este estudio es mejorar un sistema de versión de máquina avanzada usando Archerfish looking Optimization-driven intelligent ResNet50 (AHO-IResNet50) para mejorar la precisión de la identificación de faltas de servicio en bádminton, mejorando así el análisis de la puntuación de partido y la toma de decisiones para las prácticas de bádminton.
Método: se obtuvo el conjunto de datos que incorpora numerosas imágenes que capturvarias fases de

los partidos de bádminton, con las posiciones de raqueta y los movimientos de los jugadores durante el servicio, para entrenar el modelo propuesto. Un algoritmo Wavelet Discrete Wavelet rework (DWT) es utilizado para extraer las enormes características. El método propuesto incluye un algoritmo AHO para ajustar el modelo de IResNet50 para la identificación de faltas de servicio de bádminton más deseable. Este enfoque propuesto aprovecha la adaptabilidad de las estrategias de caza del pez arqupara optimizar los parámetros de IResNet50, mejorando la precisión y reduciendo errores en el reconocimiento de faltas de bádminton.
Resultados: el modelo de reconocimiento sugerido se aplica en un programa de Python. Durante la fase de análisis de resultados, evaluamos la eficacia del modelo a través de diversos parámetros junto con la precisión (94,7 %), precisión (86,7 %), recuerdo (84,9 %) y especificidad (93,5 %). Adicionalmente, se realizan análisis comparativos con las metodologías existentes para examinar la efectividad de la clasificación sugerida.
Conclusiones: los hallazgos obtenidos muestran la eficacia y superioridad del marco propuesto, disminuyendo significativamente los errores y mejorando la precisión de la identificación de faltas.

Palabras clave: El Servicio de Bádminton; Falta de Identificación; Caza de Archerfish Optimization-Driven Intelligent ResNet50 (AHO-IResNet50); Visión Artificial.

INTRODUCTION

Badminton, a quick-paced racquet sport, requires accuracy and agility from players, with the service phase playing a substantial role deciding match consequences. Referees and coaches hold to conflict with successfully recognizing service infections, which include illegal racket postures or participant actions (Pathaket al.2023). To addressthis, an innovative machine vision approach is presented.

Advancements in video analysis have led to the development of systems using machine vision techniques to improve service foul detection accuracy and efficiency. These systems use high-resolution cameras and sophisticated image processing algorithms to accurately detect and classify service fouls, such as incorrect shuttlecock positions or service height violations. The integration reduces the need for human intervention and enhances officiating consistency. In badminton, players strike the shuttlecock with a racquet to serve it to their opponent across the court to begin a rally. Some of the different types of service errors are ruled through the Badminton World Federation (BWF) (Liet al. 2023). To obtain an advantage, the shuttlecock might be struck higher than is allowed, that is the most commonplace mistake referred to as "service fault: too high" (SFTH) (Nokiharaet al.2023). Because athletes try to serve at the very high point viable, which creates a flatter trajectory that is extra difficult to return, this error is especially conventional in badminton doubles.

Human fault has historically made it hard to come across service defects, which has ended in disagreements and arguments in court (Maet al.2024). However, the inclusion of machine vision reduces such discrepancies, resulting in an extra objective appraisal of the player's serve. This device works easily with recognizing referee standards, offers real-time feedback on service violations, enabling professionals to make educated desire quickly (Vialet al.2019). Key characteristics are very well analysed in the usage of high-pace image processing, eliminating any possibility of misinterpretation.

Motivation

In badminton, accurate identification of service fouls is essential to ensure fair play and maintain the integrity of the game. Traditional methods relying on human judgment are prone to errors and inconsistencies, affecting match outcomes. Implementing a machine vision-based system can provide precise and consistent foul detection, reducing human error. This innovation aims to enhance the accuracy of match score analysis and improve decision-making during badminton practices.

Objective of the study

Study aims to create a machine vision system using Archerfish Hunting Optimization-driven Intelligent ResNet50 (AHO-IResNet50) for accurate identification of service fouls in badminton matches.

Related Works

Menonet al.2023 suggested a machine learning framework to enhance badminton player service issue detection and shuttlecock tracking. The framework integrates a player service fault detection model with a shuttlecock trajectory model, with an optimized TrackNet model achieving 90 % accuracy and 2,84 % less positioning error.

The use of computer vision-based methods for real-time video analysis in smart city applications was the main emphasis (Sabhaet al.2023). It illustrated the relevance of video analysis in smart city infrastructure and proposed a general layered architecture for video analysis. Planning authorities and scholars might gain insights from the study, which also reveals open research issues.

Rapid advancements in computer vision technology have produced notable outcomes across a range of industries. As more and more video data is being produced, computer vision research has moved from studying static images to studying video sequences, and from studying single-frame images to studying motion information in a series of multi-frame images are determined by Goudet al.2019. As a result, sophisticated motion and posture monitoring systems have been developed automatically.

Specifically focused on basketball sports, Khobdehet al.2024 suggested a technique for identifying human behaviors in uncontrolled contexts. It performs player detection and classification using a deep fuzzy LSTM (long short-term memory) network in conjunction with YOLO (you only look once). The significance of the model for basketball action identification was shown by its superior performance over baseline models in the validation of SpaceJam and Basketball-51 datasets.

The goal of Zhou et al.2022 applied deep learning to enhance intelligent football training performance. Using an action recognition system based on CNN, it analyses football player training and football robot detection. With a maximum recognition rate of 88 %, the findings demonstrated that the dual-stream network has the greatest recognition impact. The study offered a resource for the advancement of AI in sports training.

Kamaruddinet al.2020 evaluated a distributed practice learning strategy utilizing audio-visual media enhanced the foundational badminton skills using a one-group Pretest-posttest methodology of forty fourth-grade children. The ability of students to comprehend motions and instructors to provide instructional materials was made possible by the considerable improvement in learning outcomes that audio-visual media demonstrated.

The support vector machine (SVM) method was proposed by Hu 2023, as a deep learning approach for the tennis sports business to enhance the fitness of intelligent players. In comparison the method attains a classification accuracy of 97,5 % using currently available machine learning techniques, addressing delayed detection and unpredictable player motions.

In an investigation, more than 250 artificial human pose estimation-convolutional neural networks (HPE-CNNs) were examined for squash motion analysis. To identify players' feet in squash movies, (Brumannet al.2021)used five different combinations of three HPE-CNNs. To assist sports researchers, coaches, and players in selecting the optimal HPE-CNN for their use situation, they developed a ground-truth dataset and a decision flow chart.

Football players' body positioning data during penalties was analyzed by(Chakrabortyet al.2023) using YOLOv4 and OpenCV to forecast goalpost placements. The kicker's movement was tracked using an LSTM model and pose estimation. The dataset includes 205920 posture landmarks and 1560 numpy files. Before penalty shot clips, the model's accuracy rate was 50 %, with mean accuracy values of 9,6 %, 26,2 %, 52,80 % and 79,05 %.

Qiao 2021 developed a Deep Convolutional Neural Network - Long Short Term Memory (DCNN-LSTM) technique to track table tennis movements in actual time in difficult environments.The ball's trajectory was predicted using the LSTM technique, while the model uses deep reinforcement networks to extract motion data. The Deep Deterministic Policy Gradient approach yields the greatest results when it comes to feature extraction, having an accuracy rate that ranges from 89 % at maximum to 0,2475 at minimum mean square error. It offers a theoretical basis for dynamic ball identification in real-time.

METHOD

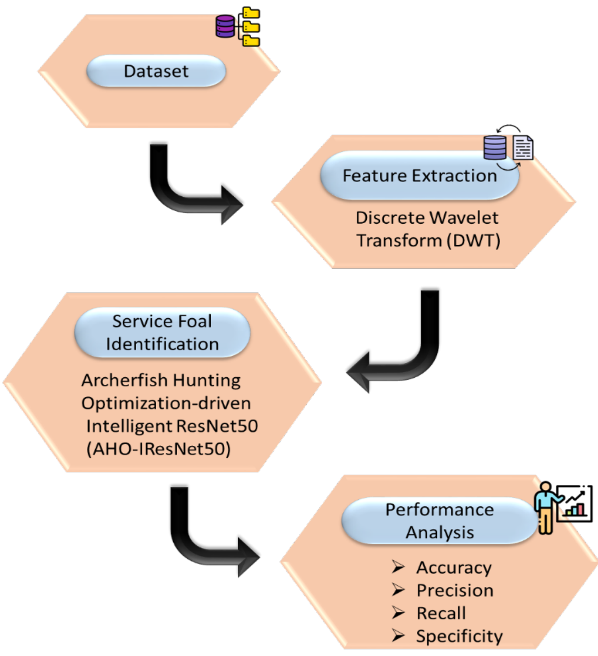

Figure 1. Methodology

The methods section describes data collection, feature extraction using the Discrete Wavelet Transform (DWT) algorithm and the novel approach AHO-IResNet50, which combines ResNet50 with Archerfish Hunting Optimisation to precisely identify badminton service fouls. Figure 1 illustrates the flow of methodology.

Data gathering

The dataset sources utilized from kaggle. The dataset includes a large number of images that show many aspects of badminton matches, such as players' movements and racket placements during service. The BWF World Tour (2018 –2021) tournament data is included in the article. A specific match from a tournament is represented by each record. [https://www.kaggle.com/datasets/sanderp/badminton-bwf-world-tour]. We split this dataset into training and testing of 80:20.

Feature extraction with Discrete Wavelet Transform (DWT) algorithm

Discrete Wavelet Transform (DWT) breaks down visual data into frequency components to improve badminton service foul detection. By using machine vision, it offers advanced analysis that increases the precision of finding violations during serves.

An image is first broken down into coefficients known as sub-bands using the suggested method, and the resulting coefficients are then compared to a threshold. Below the threshold, zero is assigned to all coefficients. In summary, a lossless compression approach is employed to encode the coefficients that exceed the threshold value.

The relative scarcity of the wavelet domain representation of the signal is the fundamental determinant of the compression properties of a given wavelet basis. The idea behind compression is some of the detail coefficients and a small number of approximation coefficients (at an appropriately defined level) can be used to approximate the regular signal component.

The following is a description of the steps in the suggested DWT-based compression algorithm:

- Split up: select a level N and a wavelet. Do a wavelet computation. Break down the signals at N levels.
- Rebuild: a threshold is chosen for every level from 1 to N, and the detail coefficients are subjected to severe thresholding.
- Threshold Detail Coefficient: wavelet reconstruction is calculated with the adjusted detail coefficients of levels 1 through N and the original approximation coefficients of level N.

Archerfish Hunting Optimization-driven Intelligent ResNet50 (AHO-IResNet50)

AHO-IResNet50 is an innovative approach that combines ResNet50 with Archerfish Hunting Optimization to identify badminton service fouls, improving officiating accuracy and match integrity.

Archerfish Hunting Optimization (AHO)

AHO-IResNet50 is an innovative method that combines ResNet50 with AHO for accurate machine vision-based badminton service foul detection, improving match integrity and officiating accuracy. Inspired by the shooting and leaping behaviors of archerfish during their insect hunts, we depict the stages of exploration and exploitation of the proposed AHO. When the objective function is properly formulated, AHO, a gradient-free optimization technique, may solve any optimization issue. We consider a dimension search space containing several archerfish.

Archerfish's position at iterations s is reported as follows, and represents the flock size, or total number of archerfish. The range of values that may be entered for each item in $W^{(j,s)}$ is as follows:

$$W^{\langle j,s\rangle} = (w_1, w_2, \dots, w_c) \qquad (1)$$

$$W^{\langle j,s\rangle} = \left(w_j\right)\epsilon\left[w_i^{max}, w_i^{min}\right](wherej \in \{1, \dots, M\}andi \in \{1, \dots, c\}.$$

Equation (2) is used to initialize the position at iteration.

$$W^{\langle j,s\rangle} = \left(\alpha_1 \times \left(w_1^{max} - w_1^{min}\right) + w_1^{min}, \dots, \alpha_c \times \left(w_c^{max} - w_c^{min}\right) + w_c^{min}\right) \qquad (2)$$

Where random values between 0 and 1 are uniformly distributed $\alpha_1 \dots . \alpha_c$.

Assuming that there is no air friction, it is calculated by the following factors: the perceiving angle (), the acceleration of gravity (), and the launch speed (). We assume that the apex of the trajectory graphic represents the location of the prey or dragonfly. The bug will fall onto the water's surface vertically when it is shot by an archerfish. Equation (3) is used by the archerfish to locate itself when it detects vibrations caused by its prey.

$$W^{\langle j,s+1\rangle} = W^{\langle j,s\rangle} + f^{-\left\|W_{prey}^{\langle l,s\rangle} - W^{\langle l,s\rangle}\right\|^2}\left(W_{prey}^{\langle j,s\rangle} - W^{\langle j,s\rangle}\right) \quad (3)$$

Where:
$W^{\langle j,s+1\rangle}$: archerfish j's next site.
$W^{\langle j,s\rangle}$: archerfish's present location.
||.||: euclidean distance.
$W_{prey}^{\langle l,s\rangle}$: location of the prey. Equation 3 is used to calculate it.
ε: an uniform distribution-produced vector of random numbers.
At the air-water contact, it depicts refraction effects.
$W^{\langle l,s\rangle}$: the place where the insect was shot by archerfish L.

$$W_{prey}^{\langle l,s\rangle} = W^{\langle l,s\rangle} + \left(0, \dots, \frac{u^2}{2h} \times sin2\theta_0, \dots., 0\right) + \varepsilon \quad (4)$$

A random integer within the range {1,……,c} indicates the entry's location, which is provided by the phrase $u^2/2h \times sin2\theta_0$.

Variable ω will be used in lieu of fraction $u^2/2h$ for simplicity's sake. It indicates how appealing an archerfish is specific to a type of prey.

Archerfishes leap at their target and seize it. Comparably, considering that there is little air friction, the archerfish's motion is determined by its perceiving angle (θ_0), gravitational acceleration (g), and launch speed (v). We assume that the peak of the trajectory diagram iswhere the prey, or dragonfly, is situated. An archerfish I uses Equation (4) to travel towards its target when it chooses to catch an insect.

$$W^{\langle j,s+1\rangle} = W^{\langle j,s\rangle} + f^{-\left\|W_{prey}^{\langle j,s\rangle} - W^{\langle j,s\rangle}\right\|^2}\left(W_{prey}^{\langle j,s\rangle} - W^{\langle j,s\rangle}\right) \quad (5)$$

$$W_{prey}^{\langle j,s\rangle} = W^{\langle j,s\rangle} + \left(0, \dots, \frac{u^2}{2h} \times sin2\theta_0, \dots.., \frac{u^2}{2h} \times sin^2\theta_0, \dots..., 0\right) + \varepsilon \quad (6)$$

In the range {1,……,c}, the entries' indicated positions according to the formulas:

$$\frac{u^2}{2h} \times sin2\theta_0 \; and \, \frac{u^2}{2h} \times sin^2\theta_0$$

Are required to be unique random values. Variable ω will be used in place of fraction $u^2/2h$ for simplicity. It characterizes an archerfish's attraction rate to a specific kind of food.

Exploration and exploitation phases will alternate depending on the value of the perceiving angle (θ_0). The ranges of perceiving angles indicate the areas of the search space that the AHO is anticipated to use (orange regions) or examine (green areas). As a result, AHO tends to use the search space better the closer θ_0 is to $\pi/2$ or $-\pi/2$ and vice versa. Equation (6) is used to produce the value of θ_0 at random.

$$\theta_0 = (-1)^a \times \alpha \times \pi \quad (7)$$

Where:
b~B (.5): distribution of Bernoulli

AHO employs an easy method to prevent becoming stuck in local optimums. Assume that the given archerfish location intend for a predetermined number of iterations at iteration is not upgraded. In this instance, a Levy Flight indicates that the matching archerfish relocates. Equations (8) and (9) are used to generate 's new location.

$$W^{\langle j,s+1\rangle} = W^{\langle j,s\rangle} + \alpha\left[\frac{v_1}{(u_1)^{1/\beta}}, \dots.., \frac{v_c}{(u_c)^{1/\beta}}\right] \quad (8)$$

$$\begin{cases} v_j \sim \mathfrak{N}(0,\sigma^2), \quad \sigma = \left(\dfrac{\Gamma(1+\beta)sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times 2^{\frac{\beta-1}{2}}}\right)^{\frac{1}{\beta}} & ,j \in \{1, \dots.., c\} \\ u_j \sim \mathfrak{N}(0,\acute{\sigma}^2), \quad \acute{\sigma} = 1 & ,j \in \{1, \dots.., c\} \end{cases} \quad (9)$$

Where:
Γ: gamma function
$N(0,\sigma^2)$: the standard deviation σ and mean μ have a normal distribution.
β: the index of power law (β = 1,5).
α: a Random integer between 0 and 1 distributed uniformly.

The following processes determine the computational complexity of AHO: candidate solution initiation, fitness evaluation, and update. The first step's computational complexity is P(M). The second step's computational complexity is $P(Iter_{max} \times M \times c)$. The computational complexity of the third step is $P(Iter_{max} \times M \times M)$. $P(M \times Iter_{max} \times (M+c) \times 1)$ is the computational complexity of AHO as a result.

Intelligent ResNet50 (IResNet50)

Intelligent ResNet50 uses advanced machine vision to accurately detect badminton service fouls, utilizing deep learning algorithms to analyze player movements and serve mechanics, thereby enhancing game fairness.

The idea of residual blocks was used in this design to solve the problem of exploding/ vanishing gradients. "Skip connections" is the strategy we use in this network. Bypassing a few intermediate levels, the skip connection links layer activations to subsequent layers. Figure 2 shows the ResNet50 framework. Consequently, rather than using, for example, equation (10) represents the first mapping of J(w).

$$\mathcal{F}(w) := J(w) - w which gives J(w) := \mathcal{F}(w) + w \qquad (10)$$

Conventional CNNs are effective at representing features, although their receptive fields are limited by the size of their convolution kernels. Therefore, IResNet-50 has limited global expression capability and specific data loss. Initially, the residual unit receives a second focus from the Squeeze-and Excitation (SE) attentiveness to examine various feature channels CNN each block boxes max pool and avg pool are worked in the IResNet5. The network's performance can be enhanced by using the ranger optimizer to train the model. Thirdly, the label smoothed cross entropy loss function is substituted for the loss function to attempt to address the overestimation classification process to protect memory, the IResNet-50's levels are more lightweight.

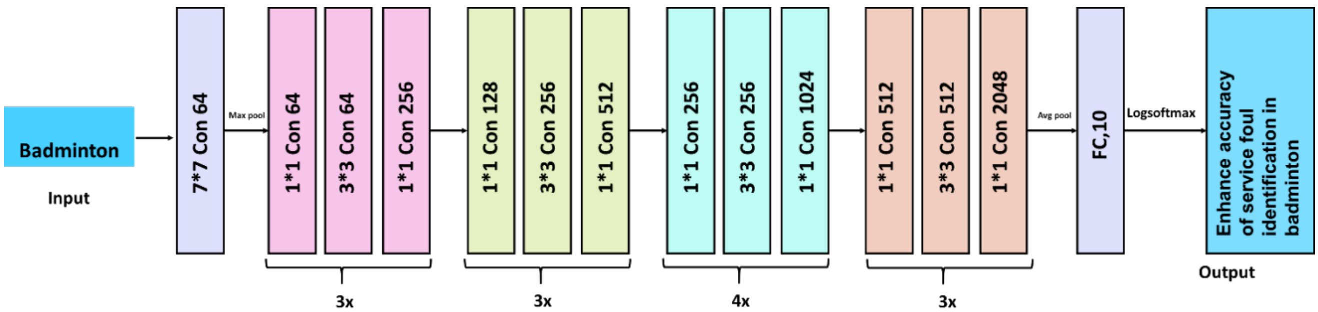

Figure 2. ResNet50 Architecture

The defined version architecture offers a comprehensive residual community (ResNet) framework in particular configured for an assignment that likely entails analyzing or classifying facts from the prostate dataset. It contains multiple stages of residual blocks, each designed with a bottleneck structure featuring convolutional layers of various filter sizes and strides, interspersed with batch normalization and ReLU (Rectified Linear Unit) activation layers. These blocks progressively increase in complexity and abstraction through distinct tiers, with adjustments in filter-out sizes and strides to capture hierarchical features successfully. Furthermore, the model contains a region proposal network (RPN) together with class and regression layers for place idea, followed by additional layers consisting of RoIAlign (Region of Interest Align) and mask class. Substantially, the optimizer strategy is sophisticated, employing a mixed technique of Adam and SGD (Stochastic Gradient Descent) optimizers with one-of-a-kind mastering costs for precise epochs, aimed toward attaining the most appropriate convergence and generalization. This model architecture showcases a meticulous layout tailored for tasks annoying each characteristic extraction and precise localization, making it suitable for programs together with item detection or medical photograph evaluation in the context of prostate dataset analysis.

RESULTS

A computer with a minimum of 8GB RAM and 2GB GPU (Graphic Processing Unit) for real-time processing powers an experimental badminton service foul detection system that combines machine vision with a high-speed camera (1080p, 60fps) and software such as OpenCV. The effectiveness of the suggested and existing approaches was assessed in terms of (accuracy, precision, recall, and specificity). Compared to the suggested method, existing methods include Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) and CNN+GRU (Convolutional Neural Networks + Gated recurrent unit) w/ video(Fang et al. 2024), CNN, RNN (Thamaraimanalan et al. 2020). The machine vision-based badminton service foul system tested with greater accuracy rate and lower of loss rate. Figure 3 shows the outcome of accuracy and loss.

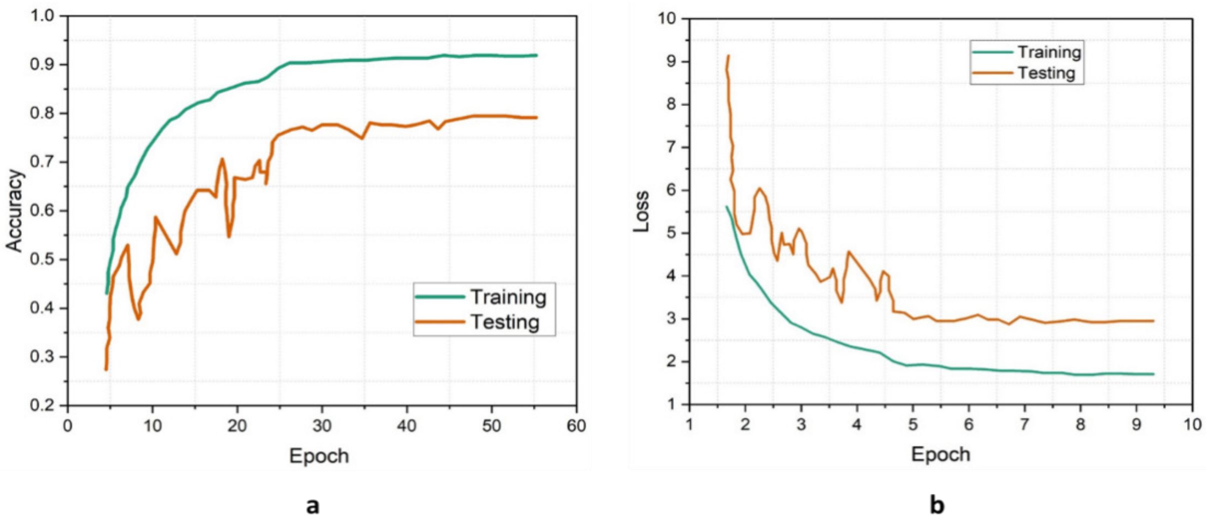

Figure 3. Outcome of accuracy and loss

Accuracy

The fraction of accurately determined service fouls vs non-fouls across all instances. It assesses overall accuracy. In a comparative analysis, our suggested approach AHO-IResNet50 (94,7 %) outperforms the existing approaches CNN & RNN (77,4 %), and CNN (87,6 %). Table 1 and figure 4 show the outcome of accuracy.

$$Accuracy = \frac{TP+TN}{TotalInstance} \qquad (11)$$

Table 1. Value of Accuracy

Model	**Accuracy (%)**
CNN & RNN	77,4
CNN	87,6
AHO-IResNet50 [Proposed]	94,7

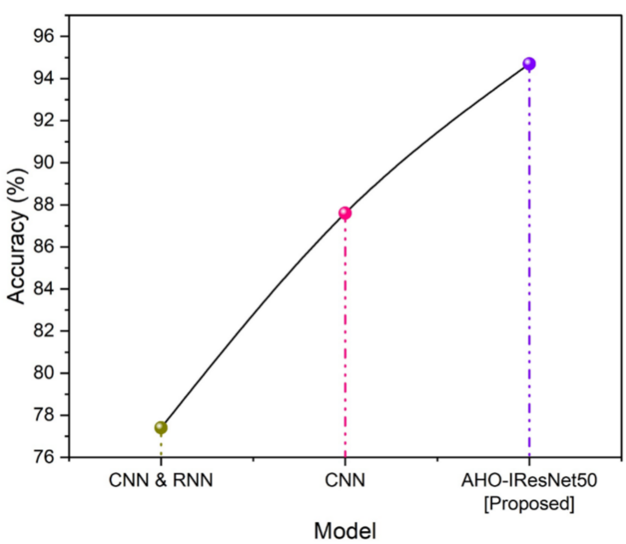

Figure 4. Outcome of Accuracy

Precision

The proportion of successfully discovered service fouls out of all cases that are classified as fouls. The capacity of the model to prevent false positives is measured.Our suggested solution outperforms AHO-IResNet50 (86,7 %) of the existing ones when compared to CNN & RNN (79 %), and CNN+GRU w/ video (63 %). Table 2 and figure 5 show the outcome of precision.

$$Precision = \frac{TP}{TP+FP} \quad (12)$$

Table 2. Value of Precision

Model	Precision (%)
CNN & RNN	79,0
CNN+GRU w/ video	63,0
AHO-IResNet50 [Proposed]	86,7

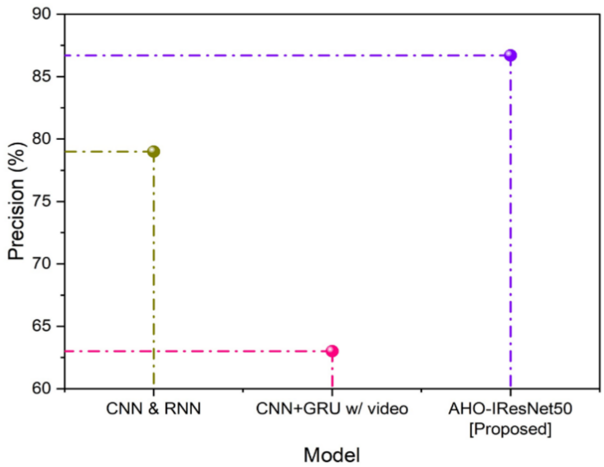

Figure 5. Outcome of Precision

Recall

The fraction of accurately identified service fouls to total fouls. It assesses how effectively the model is responsible for every positive instance. Our proposed strategy AHO-IResNet50 (84,9 %) performs better than the existing approaches CNN & RNN (75 %), and CNN (76,8 %) in a comparative analysis. Table 3 and figure 6 show the outcome of recall.

$$Recall = \frac{TP}{TP+FN} \quad (13)$$

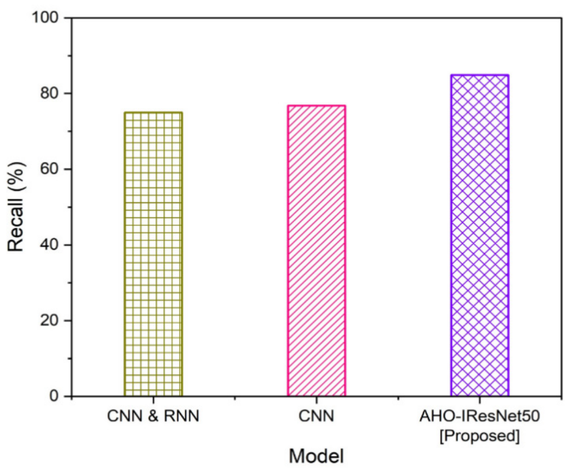

Figure 6. Outcome of Recall

https://doi.org/10.56294/sctconf2024.760

Table 3. Value of Recall	
Model	**Recall (%)**
CNN & RNN	75,0
CNN	76,8
AHO-IResNet50 [Proposed]	84,9

Specificity

The percentage of accurately recognized non-fouls out of all real non-fouls. Our proposed method AHO-IResNet50 (93,5 %) performs better than the existing methods CNN (86,2 %), and RNN (80,7 %). Table 4 and figure 7 shows the outcome of Specificity.

$$Specificity = \frac{TN}{TN+FP} \quad (14)$$

Table 4. Value of Specificity	
Model	**Specificity (%)**
CNN	86,2
RNN	80,7
AHO-IResNet50 [Proposed]	93,5

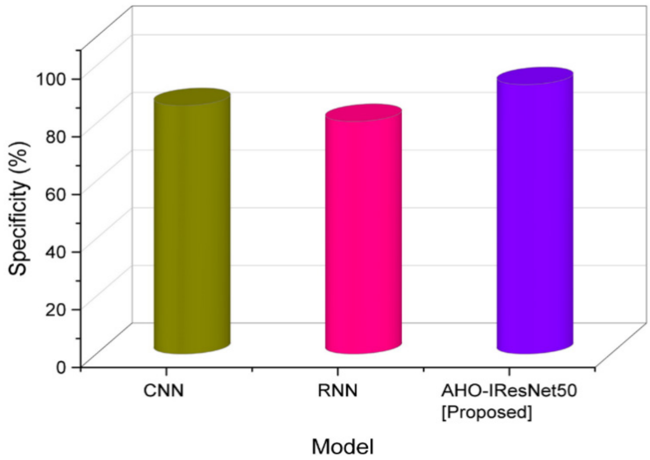

Figure 7. Outcome of Specificity

DISCUSSION

While CNNs are good at collecting spatial data, they might not be able to handle the time dynamics that are necessary for precisely identifying badminton service failures. They also need a lot of labeled data, which might be hard to get by. RNNs are slower to train in general and are less successful in resolving long-term dependencies in service sequences due to concerns with vanishing gradients. Better temporal management can be achieved by combining CNNs with GRUs, however this combination can be computationally demanding and complicated. The likelihood of overfitting is increased by this complexity, which might make it more difficult for the model to generalize to new service scenarios. By using sophisticated image analysis to increase the accuracy of service fault detection, AHO-IResNet50 improves the badminton service foul system. Its refined ResNet50 design offers more rapid processing and accurate rule violation detection.

CONCLUSIONS

Study highlights the effectiveness of using the Archerfish Hunting Optimization-driven Intelligent ResNet50 (AHO-IResNet50) to enhance foul recognition in badminton. By integrating advanced image processing techniques and feature extraction methods, the AHO-IResNet50 model addresses significant challenges in maintaining match integrity. The innovative approach of combining Discrete Wavelet Transform with a fine-tuned ResNet50 model, driven by optimization algorithms, demonstrates a substantial improvement in recognizing service fouls. This

https://doi.org/10.56294/sctconf2024.760

advancement is crucial for refining decision-making processes and reducing errors in match score analysis, leading to fairer and more transparent badminton games. The successful implementation of this methodology in practice shows its potential to transform how fouls are identified, aligning with the objective of creating a robust system for accurate service foul detection. The study underscores the broader applicability of machine vision in enhancing the integrity of sports competitions.

Despite the mornings promising findings, the suggested method might struggle to reliably detect service fouls in certain lightning circumstances or with rapid player movement. Further development and integration of real-time feedback mechanisms might improve the system's suitability for live matches, opening the path for its use in professional badminton competitions.

BIBLIOGRAPHIC REFERENCES

1. Pathak P, Jilani M, Stynes P. A Machine Learning Framework for Shuttlecock Tracking and Player Service Fault Detection. InDeep Learning Theory and Applications: 4th International Conference, DeLTA 2023, Rome, Italy, July 13–14, 2023, Proceedings 2023 Jul 30 (p. 71). Springer Nature. DOI: https://doi.org/10.1007/978-3-031-39059-3_5

2. Li T, Lin J, Pan L, Wang Z. Badminton Detection Using Lightweight Neural Networks for Service Fault Judgement. InInternational Conference on Bio-Inspired Computing: Theories and Applications 2023 Dec 15 (pp. 182-194). Singapore: Springer Nature Singapore. DOI: https://doi.org/10.1007/978-981-97-2275-4_15

3. Nokihara Y, Hachiuma R, Hori R, Saito H. Future Prediction of Shuttlecock Trajectory in Badminton Using Player's Information. Journal of Imaging. 2023 May 11;9(5):99. DOI: https://doi.org/10.3390/jimaging9050099

4. Ma E, Kabala ZJ. Refereeing the Sport of Squash with a Machine Learning System. Machine Learning and Knowledge Extraction. 2024 Mar 5;6(1):506-53. DOI: https://doi.org/10.3390/make6010025

5. Vial S, Cochrane J, J. Blazevich A, L. Croft J. Using the trajectory of the shuttlecock as a measure of performance accuracy in the badminton short serve. International Journal of Sports Science & Coaching. 2019 Feb;14(1):91-6. DOI: https://doi.org/10.1177/1747954118812662

6. Menon A, Siddig A, Muntean CH, Pathak P, Jilani M, Stynes P. A machine learning framework for shuttlecock tracking and player service fault detection. InInternational Conference on Deep Learning Theory and Applications 2023 Jul 13 (pp. 71-83). Cham: Springer Nature Switzerland. DOI: https://doi.org/10.1007/978-3-031-39059-3_5

7. Sabha A, Selwal A. Towards machine vision-based video analysis in smart cities: a survey, framework, applications and open issues. Multimedia Tools and Applications. 2023 Aug 9:1-52.DOI: https://doi.org/10.1007/s11042-023-16434-2

8. Goud PS, Roopa YM, Padmaja B. Player performance analysis in sports: with fusion of machine learning and wearable technology. In2019 3rd International Conference on Computing Methodologies and Communication (ICCMC) 2019 Mar 27 (pp. 600-603). IEEE. DOI: https://doi.org/10.1109/ICCMC.2019.8819815

9. Khobdeh SB, Yamaghani MR, Sareshkeh SK. Basketball action recognition based on the combination of YOLO and a deep fuzzy LSTM network. The Journal of Supercomputing. 2024 Feb;80(3):3528-53. DOI: https://doi.org/10.1007/s11227-023-05611-7

10. Zhou D, Chen G, Xu F. Application of Deep Learning Technology in Strength Training of Football Players and Field Line Detection of Football Robots. Frontiers in Neurorobotics. 2022 Jun 29;16:867028. DOI: https://doi.org/10.3389/fnbot.2022.867028

11. Kamaruddin I, Nur M, Sufitriyono S. Distributed practice learning model using audiovisual media for teaching basic skills of badminton. Journal of Educational Science and Technology. 2020;6(2):224-32. DOI: https://doi.org/10.26858/est.v6i2.13801

12. Hu R. IoT-based analysis of tennis player's serving behavior using image processing. Soft Computing. 2023 Oct;27(19):14413-29. DOI: https://doi.org/10.1007/s00500-023-09031-w

13. Brumann C, Kukuk M, Reinsberger C. Evaluation of open-source and pre-trained deep convolutional neural networks suitable for player detection and motion analysis in squash. Sensors. 2021 Jul 2;21(13):4550. DOI: https://doi.org/10.3390/s21134550

14. Chakraborty D, Kaushik MM, Akash SK, Zishan MS, Mahmud MS. Deep Learning-Based Prediction of Football Players' Performance During Penalty Shootout. In2023 26th International Conference on Computer and Information Technology (ICCIT) 2023 Dec 13 (pp. 1-6). IEEE. DOI: https://doi.org/10.1109/ICCIT60459.2023.10441247

15. Qiao F. Application of deep learning in automatic detection of technical and tactical indicators of table tennis. PLoS One. 2021 Mar 9;16(3):e0245259. DOI: https://doi.org/10.1371/journal.pone.0245259

16. Fang J, Yeung C, Fujii K. Foul prediction with estimated poses from soccer broadcast video. arXiv preprint arXiv:2402.09650. 2024 Feb 15. DOI: https://doi.org/10.48550/arXiv.2402.09650

17. Thamaraimanalan T, Naveena D, Ramya M, Madhubala M. Prediction and classification of fouls in soccer game using deep learning. Ir. Interdiscip. J. Sci. Res. 2020 Jan;4:66-78.

FINANCING
No financing.

CONFLICT OF INTEREST
The authors declare that there is no conflict of interest.

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