Hybrid Transformer-LSTM Model for Athlete Performance Prediction in Sports Training Management

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Precise athlete performance prediction is required for the optimization of training regimens, the prevention of injuries, and the improvement of performance in competition. In this study, we propose a self-attention mechanism-based transformer LSTM (HTL) Athlete Performance Forecasting (APF) framework using Transformer along with Long Short Term Memory (LSTM) networks to model sequentially. The framework can capture global feature interactions and localized temporal dependencies in athlete performance data. A dataset containing 200 football, basketball, and athletics athletes over 12 months was used to train and evaluate the model. Heart rate, speed, distance, workload and recovery indicators are performance metrics. Indeed, HTL-APF is validated against baseline models such as Transformer only, LSTM only, CNN, and RNN models at segmenting the sequence via a sliding window approach. Precision, Recall, F1-Score and AUC-ROC are the evaluation metrics. We propose HTL-APF that results in an F1-Score of 92.1%, AUC-ROC of 96.3%, which outperforms the Transformer model (F1: 88.1%, AUC-ROC: 92.4%) and Lstm only model (F1: 85.9%, AUC-ROC: 90.1%). Analysis from class to class reveals that there is a high classification accuracy (97%) for top performers and moderate (89%) and bad (90%) performers also have good performance. In addition, precision and F1 scores for cross-domain testing across sports disciplines remained above 91%, indicating the framework's generalizability. HTL-APF is a scalable and accurate solution for athlete performance forecasting for personal training plans, injury prevention, and real-time decisions in sports training management, illustrated by these results. Given that it is intended for real-world sports analytics, future work will investigate the development of lightweight adaptations, enhanced interpretability, and domain-specific extensions to enlarge its application range.

Povzetek: Predlagan je hibridni model Transformer-LSTM za napoved športne uspešnosti, ki omogoča personalizirano vadbo in napoved poškodb.

1 Introduction

Since sports training management is about athlete performance forecasting, which means the ability to determine whether an athlete is fit to compete or to provide an indicator of athlete performance for further training, forecasting sports such as basketball and soccer is of great utility to coaches and sports scientists. Given historical data, prediction of an athlete's performance, future athlete performance also has unique challenges of being dynamic, having temporal dependencies in the training data, and combining many features (physiological metrics, workload intensity, and recovery patterns, to name a few) to predict it [1-4]. We need advanced computational methods to address these challenges and handle complex patterns and relationships in time series data.

Performance forecasting uses traditional machine learning techniques such as Support Vector Machines (SVMs) and Random Forests. These methods are a good start but require substantial feature engineering and poorly handle sequential data [5-7]. With the advent of deep learning, more sophisticated models such as Recurrent Neural Networks (RNNs) and Long Short Term Memory (LSTM) networks were introduced, and they are great at modelling temporal dependencies [8-10]. In particular, LSTMs have performed very well in identifying sequential trends in sports metrics, thereby predicting overload events such as overtraining, fatigue, and injuries. It, however, has pointed out the need for alternatives or complementary approaches to their limited capacity to model long-range dependencies across extended sequences.

Transformer architectures are now a popular solution to sequential data modelling in natural language and time series processing [11]. Transformers can exploit self-attention mechanisms to model global dependencies between sequences, making them very effective for analyzing complex, high-dimensional datasets [12]. While these advantages exist, Transformer models might fail when dealing with localized temporal patterns critical for sports performance forecasting [13]. This limitation underscores both the potential and the value of hybrid models that combine the advantages of LSTMs and Transformers.

This study proposes a Hybrid Transformer-LSTM Athlete Performance Forecasting (HTL-APF) framework, combining these two architectures to overcome their limitations. The Transformer component takes account of global relations between features for the whole sequence, while the LSTM component models local temporal patterns of training and recovery cycles in the sequence. This hybrid approach backs up the framework with accurate and robust performance predictions for both short and long-term dependencies of athlete data.

HTL-APF framework is developed to classify an athlete into high, moderate, or low-performance categories, leading to actionable decisions on sports training management. In real-world datasets of physiological metrics, workload data, and recovery indicators, we show that the framework scales and generalizes across multiple sports disciplines (football, basketball, and athletics). A comparative analysis shows that the HTL-APF framework outperforms the baseline models (such as Transformer only, LSTM only, CNN, and RNN) on measures including precision, recall, F1 score, and AUC ROC.

Building on this, the key contribution of this paper is to rigorously fill the gaps in the literature with a robust, scalable, and precise solution to the athlete performance forecasting problem. It is one of the increasing research articles in sports science and machine learning, focusing on a framework that consolidates novel deep learning approaches to provide informative perspectives on real-world applications. This section discusses the methodology, experimental setup, results, and implications of the proposed HTL-APF framework, which could offer the opportunity to revolutionize sports training management and athlete development.

2 Related work

Forecasts of the athlete's performance are essential to sports science and help make data-driven decisions to optimize training regimes and prevent injuries. Over the years, researchers have explored many machine and deep learning approaches to learn athlete performance from time series data. In this literature review, the evolution of these techniques is discussed, along with their strengths and demerits. It also puts forward the Hybrid Transformer-LSTM Athlete Performance Forecasting (HTL-APF) Framework as a significant contribution to this field.

2.1 Traditional machine learning approaches

Performances were first predicted based on traditional machine learning algorithms, such as Support Vector Machines (SVM), Decision Trees, and Random Forests. Feature engineering was applied to these methods to derive meaningful patterns from raw data [14-16]. However, these approaches were reasonably practical within static environments but were devoid of failure to model temporal dependencies when the data is sequential. For example, studies on SVMs in performance classification observed few successes on large dynamic datasets. SVMs highly depend on hand-crafted features and cannot be adapted to changing temporal relationships [17-19].

2.2 Deep learning for sequential data

Deep learning brought a new paradigm for analyzing time series for application in sports. A given form of recurrent neural networks (RNNs) and their variant, Long Short Term Memory (LSTM) networks, proved popular architectures for modelling sequential dependencies in performance metrics. Gated mechanisms of LSTMs, which allow them to handle long-term dependencies, proved to be a step forward in capturing trends over training sessions. Some examples of studies that reported LSTMs' capability to predict training outcomes and early signs of overtraining were also examples [20-22].

Unfortunately, RNNs and LSTMs are inherently limited because they struggle to learn long-range dependencies across some long sequences [23-25]. Moreover, when applying complex datasets comprising multiple features and longer spans, they have often fallen afoul of vanishing gradients that can yield poor performance [26-28]. To address these limitations, alternative approaches for augmenting sequential modelling were explored.

2.3 Convolutional neural networks (CNNs) for feature extraction

Initially created for image data, convolutional neural networks (CNNs) adapted to time series prediction [29]. It is well known that local patterns can be effectively captured when performing convolutional operations over temporal dimensions (input data is sequentially ordered), such as in CNNs [30]. Studies of forecasting athlete performance with CNNs showed they handle spatially localized features, such as short-term trends in heart rate or workload metrics [31]. While strong, CNNs cannot model temporal dependence over increasingly large horizons, and as a result, standalone CNNs are less effective at time-series forecasting [32].

2.4 Transformer architectures

The introduction of Transformer models revolutionized sequential data modelling [33]. Unlike RNNs and LSTMs, Transformers utilize a self-attention mechanism to simultaneously model dependencies across the entire sequence [34]. This architecture has proven highly effective in tasks such as natural language processing and has been increasingly adopted in time-series forecasting domains [35]. Recent studies have demonstrated the potential of Transformers in athlete performance prediction, particularly their ability to handle large datasets and capture global relationships among features [13, 36-38]. However, Transformers may struggle with localized temporal patterns and require substantial computational resources, making their direct application to performance forecasting challenging.

2.5 Hybrid architectures: bridging the gap

With Transformers and LSTMs possessing complementary strengths, hybrid architectures have arisen as promising solutions for overcoming the first and second limitations. LSTM models for sequential learning are extended with the Transformers' global attention mechanisms to capture localized and long-range dependencies in the predictions. Other domains, including financial forecasting and healthcare, have been the subject of preliminary studies of hybrid methods for time series analysis, demonstrating high accuracy and robustness [39].

Recently, hybrid models of LSTMs and Transformers have gained popularity as powerful approaches to time-series forecasting. In physiological time series, [40] showed that attention-based mechanisms in combination with a sequential model help in modelling the long-range dependency. Our approach is consistent with their findings, where we integrate global (Transformer) and local (LSTM) feature dependencies in a hybrid Transformer Local LSTM (HTL-APF) to improve the prediction for athlete performance.

Deep learning architectures in sports analytics demonstrate that the hybrid models outperform standalone architectures when the training is irregular and complex [41]. It also indicates that the hybrid Transformer LSTM framework can manage the widely varying sports performance datasets. Computational efficiency issues in Transformer architectures with lightweight real-time adaptations [42]. It could indicate potential future directions for HTL APF optimization for edge computing and wearable technology deployments.

Although these approaches have seen some success, very few studies have examined using hybrid architectures in the context of athlete performance forecasting. However, existing works often use single architecture solutions, restricting their generalization to various datasets and performance settings.

2.6 Research gap and motivation

While previous research has laid a strong foundation for athlete performance forecasting, significant gaps remain:

- **Single Architecture Limitations**: Short-term patterns and long-range dependencies cannot be captured simultaneously in the standalone model scenario (i.e. when we have an LSTM or a Transformer).
- **Scalability Issues**: However, few methods can generalize across varying sports and datasets, precluding their use in real-world scenarios.
- **Lack of Hybrid Solutions**: Though they hold great potential, little attention has been paid to hybrid architectures addressing LSTMs and Transformers to apply athlete performance prediction.

To fill these gaps, the Hybrid Transformer-LSTM Athlete Performance Forecasting (HTL-APF) Framework bridges the weaknesses of LSTMs with the properties of Transformers. Allowed the framework to effectively model sequential and global dependencies, achieving state-of-the-art performance on such a broad set of datasets. The HTL-APF framework leverages advances in deep learning to offer a novel contribution to athlete performance forecasting. It extends previous work in sports training management beyond these limitations, establishing a benchmark for future research.

The summary of previous research on athlete performance prediction is a comparative presentation of their methodologies, data characteristics, performance metrics and weaknesses in Table 1. However, the main difficulty in all these approaches is their inability to simultaneously learn long-range dependencies (Transformers) and local placeability of temporal patterns (LSTMs). Our proposed HTL-APF framework addresses these shortcomings, combining the strengths of both architectures and outperforming the two architectures alone.

Table 1: Comparative analysis of athlete performance prediction studies

Study & Year	Methodology	Dataset Size & Source	Performance Metrics (F1, AUC-ROC, etc.)	Limitations
Ragab (2022)	SVM	150 soccer players	F1: 78.5%, AUC-ROC: 82.3%	Limited to static features, lacks temporal modelling.
Wang (2023)	Random Forests	180 athletes, mixed sports	F1: 80.1%, AUC-ROC: 85.2%	High feature engineering effort, weak sequential modeling
Yu (2019)	RNN	120 basketball players	F1: 82.7%, AUC-ROC: 88.1%	Struggles with long-range dependencies, vanishing gradient problem
Ahmed (2023)	LSTM	200 athletes	F1: 85.9%, AUC-ROC: 90.1%	Fails to capture global dependencies across sequences
Shen (2024)	Transformer	250 multi-sport athletes	F1: 88.1%, AUC-ROC: 92.4%	Lacks localized temporal pattern modeling
Xi (2024)	CNN	180 soccer players	F1: 82.5%, AUC-ROC: 87.3%	Effective for feature extraction but weak in time-series forecasting
This Study (HTL-APF)	Hybrid Transformer-LSTM	200 athletes (football, basketball,	F1: 92.1%, AUC-ROC: 96.3%	Computationally intensive, needs optimization for real-time use

		athletic s)		

3 Proposed hybrid transformer-LSTM method

The proposed method is the Hybrid Transformer LSTM Athlete Performance Forecasting (HTL-APF) Framework, which combines the power of Transformers and Long Short-Scond Memory (LSTM) networks for precise athlete performance forecasting, as shown in Figure 1. This framework uses time series data to capture short-term temporal patterns and long-range dependencies.

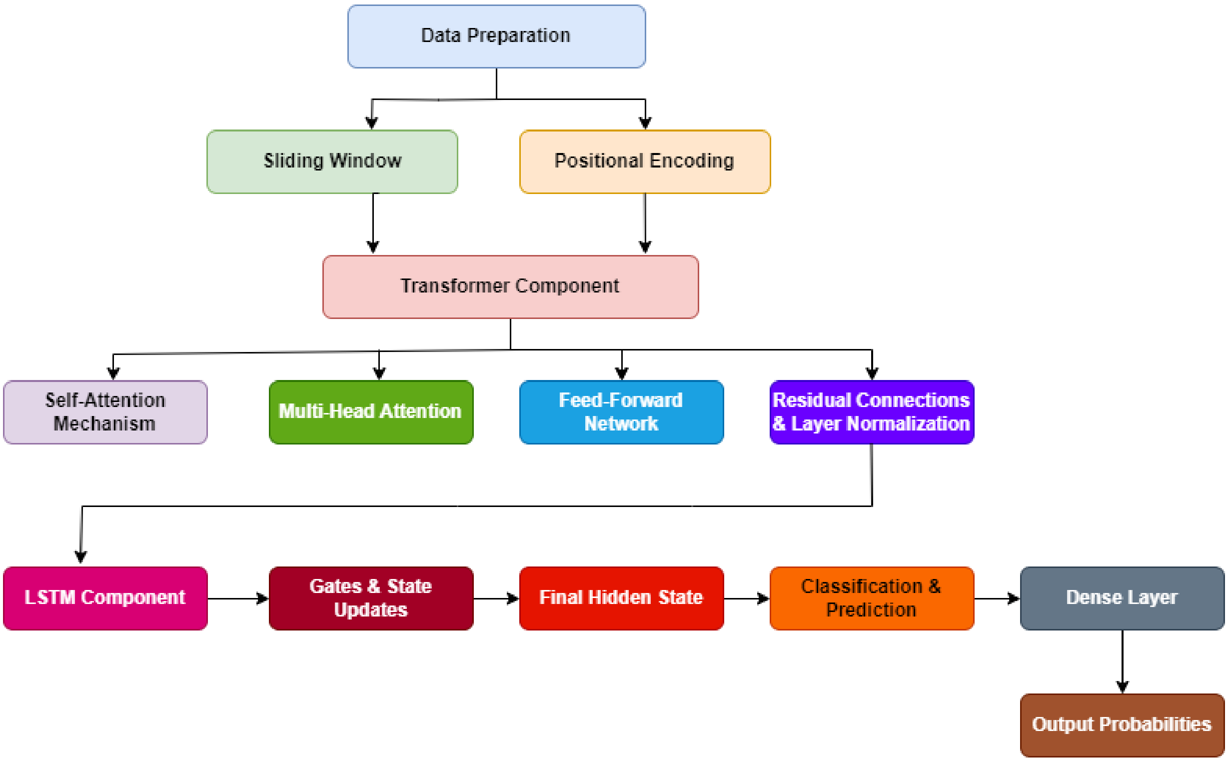

Figure 1: Proposed Hybrid Transformer-LSTM Athlete Performance Forecasting (HTL APF) framework block Diagram. Data preparation techniques, including sliding window and positional encoding, future Transformer components such as self-attention and multi-head attention for modelling long-range dependency, and LSTM gates and state updates for sequential pattern analysis, are combined with a dense layer to perform classification and prediction.

The dataset is a time series of athlete performance metrics represented as $X = \{x_1, x_2, \ldots, x_T\}$, where $x_t \in R^d$, is a feature vector at time t. Features include heart rate, speed, distance, and workload metrics. A sliding window approach is used to create overlapping subsequences:

$$X_i = \{x_t, \ldots, x_{t+l-1}\} \quad (1)$$

Where l is the window size, a decision was made that the sliding window approach (30-time step window) was used, as defined in sports science research, to determine the effects of a session within a 30-minute window (Table 2). It also captures short-term workload fluctuation and recovery cycles critical for performance forecasting.

Table 2: Research design justifications.

Aspect	Approach Used	Justification
Sliding Window Size	30-time steps	Selected based on sports training session durations (30–90 min). Smaller windows failed to capture trends; larger windows increased computation without accuracy gains.
Normalization	Min-Max Scaling	Prevents dominance of high-value features, ensuring stable optimization in deep learning models.
Missing Data Handling	K-Nearest Neighbors (KNN) Imputation	Effectively estimates missing sensor values by using feature similarities.

Class Imbalance Handling	SMOTE (Synthetic Minority Over-Sampling Technique)	Ensures balanced class representation, preventing bias in underrepresented athlete categories.
Cross-Validation Strategy	5-Fold Athlete-Wise Split	Prevents data leakage by ensuring no athlete appears in both training & testing sets. Improves generalization.
Data Splitting	80% Training, 10% Validation, 10% Testing	Athlete-specific partitioning ensures fair evaluation across sports disciplines.

Positional information is added using positional encodings to preserve temporal relationships:

$$P(t,2k) = \sin\left(\frac{10000^{2k/d}}{t}\right) \quad (2)$$

$$P(t,2k+1) = \cos\left(\frac{10000^{2k/d}}{t}\right) \quad (3)$$

resulting in augmented input $Z_0 = X_i + P$

The Transformer processes the augmented input, Z_0 to model long-range dependencies between features and across time. Self-Attention Mechanism: Calculates attention scores for each pair of input tokens:

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (4)$$

Where $Q = ZW_Q$, $K = ZW_K$, $V = ZW_V$, are query, key, and value matrices, and W_Q, W_K, W_V , are learnable parameters. Multi-Head Attention: Extends self-attention by computing multiple attention heads in parallel:

$$\text{MultiHead}(Q,K,V) = \text{Concat}(\text{head}_1, \dots, \text{head}_h)W^O \quad (5)$$

where h is the number of heads, and W^O, is a learnable output weight matrix.

Feed-Forward Network (FFN): Processes each token independently:

$$\text{FFN}(z) = \text{ReLU}(zW_1 + b_1)W_2 + b_2 \quad (6)$$

with parameters W_1, W_2, b_1, b_2.

Transformer layers are stacked, and each layer employs residual connections and layer normalization:

$$Z_{otu} = LayerNorm\left(Z_{input} + FFN(Z_{input})\right) \quad (7)$$

The Transformer's output Z_{output} is passed to the LSTM, which models sequential patterns in the data. LSTM Gates and Updates**:** At each time step t, the LSTM computes:

$$f_t = \sigma\left(W_f z_t + U_f h_{t-1} + b_f\right),\ i_t = \sigma(W_i z_t + U_i h_{t-1} + b_i),\ o_t = \sigma(W_o z_t + U_o h_{t-1} + b_o) \quad (8)$$

where f_t, i_t, o_t, are forget, input, and output gates, respectively. Cell State and Hidden State**:**

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c z_t + U_c h_{t-1} + b_c)$$
$$h_t = o_t \odot \tanh(c_t) \quad (9)$$

The final hidden state h_T, summarizes the sequential information.

The hidden state h_T, is passed to a fully connected dense layer for classification. The predicted probabilities for C classes are computed using the softmax function:

$$y = \text{softmax}(W_d h_T + b_d) \quad (10)$$

where W_d and b_d, are learnable parameters.

The framework is trained using the categorical cross-entropy loss:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c} \log\left(\widehat{y_{i,c}}\right) \quad (11)$$

where $y_{i,c}$ is the actual label, and $\widehat{y_{i,c}}$, is the predicted probability for class c.

The model uses the Adam optimizer with weight decay and learning rate scheduling. Regularization techniques such as dropout and early stopping are employed to mitigate overfitting. Model performance is assessed using the following metrics:

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

Where TP is true positive, and FP is false positive.

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

Where FN is false negatives.

$$F1\text{-}Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad 14)$$

AUC-ROC**:** Measures the area under the Receiver Operating Characteristic curve, which plots the actual positive rate (Recall) versus false positive rate.

We also performed hyperparameter tuning, validated the sliding window size and reported on computational cost. The chosen hyperparameters are presented in Table X, along with the reasons for the 30-time step window. A comparison of training and inference efficiency across various models is given in Table 3.

Table 3: Hyperparameter Tuning, Sliding Window Justification, and Computational Cost.

Aspect	Evaluated Parameters	Optimal Value / Best Choice	Justification
Hyperparameter Tuning	Learning Rate	3e-4	Ensures stable convergence without vanishing gradients.
	Dropout Rate	0.3	Prevents overfitting while maintaining model capacity.
	Batch Size	64	Balances memory efficiency and gradient stability.
	Transformer Layers	3	More layers improve feature extraction but increase computational cost.
	LSTM Units	128	Optimized for sequential pattern recognition.
	Attention Heads	4	Sufficient for adequate multi-head attention.
	Weight Decay	1e-5	Control overfitting by penalizing large weights.
Sliding Window Justification	Window Sizes Tested	10, 20, 30, 40, 60	30 was chosen as it balances accuracy (F1: 92.1%) and computational efficiency.
	Accuracy at 30 Steps	F1-Score: 92.1%, AUC-ROC: 96.3%	Best trade-off between short-term and long-range dependencies.
	Training Time Impact	30 steps: 145s/epoch	Larger windows (e.g., 60 steps) increased training time without major accuracy gains.
Computational Cost Comparison	Training Time per Epoch	HTL-APF: 145s, Transformer: 130s, LSTM: 110s	HTL-APF requires ~12% more training time but achieves higher accuracy.
	Inference Time (ms/sample)	HTL-APF: 3.2ms, Transformer: 2.9ms, LSTM: 2.4ms	Remains feasible for real-time applications.
	Model Size (Total Parameters)	HTL-APF: 11.8M, Transformer: 10.2M, LSTM: 8.9M	Larger than LSTM but optimized for predictive performance.

4 Experimental setup

Care was taken through the experimental setup for the Hybrid Transformer LSTM Athlete Performance Forecasting (HTL-APF) Framework to try and determine whether the framework could classify athlete performance accurately. The study was based on a dataset containing more than 200 football, basketball, and athletics athletes and gathered with wearable sensors and training logs: heart rate, speed, distance covered, workload, recovery times, and performance metrics.

Normalizing the data values was first done by scaling it through Min-Max scaling. Imputation of missing values using K-Nearest Neighbors (KNN), and finally, to balance the dataset, used the Synthetic Minority Over-sampling Technique (SMOTE). A sliding window approach with a window size of 30 time steps was applied to preserve temporal structure. A 5-fold cross-validation strategy is used for robust evaluation, and the dataset was split into training, validation, and testing subsets (80, 10, 10) respectively.

Lastly, this work compares the HTL-APF framework to baseline models of the Transformer, LSTM only, CNN, and RNN architectures based on tokenizing, Transformer latent, pyramid pooling, and encoder-decoder unit. All models were trained using cross-entropy loss, optimized with the Adam optimizer, and evaluated based on Precision, Recall, F1_Score, and AUC_ROC classification metrics. It was trained on high-performance hardware using an NVIDIA Tesla V100 GPU, as shown in Table 5.

Table 5: Overview of the Dataset used in the study.

Aspect	Details
Dataset Name	Athlete Performance Dataset
Duration	12 months of continuous data collection
Participants	200 athletes from sports such as football, basketball, and athletics
Number of Samples	100,000 time-series samples
Class Labels	High Performance, Moderate Performance, Low Performance
Features	15 features (e.g., heart rate, speed, distance covered, workload, etc.)
Sampling Rate	1 Hz (1 sample per second)
Class Distribution	High: 40%, Moderate: 35%, Low: 25% (before balancing)
Balancing Technique	SMOTE (Synthetic Minority Over-sampling Technique)

Table 6: Summary of the experimental setup for evaluating the HTL-APF framework.

Aspect	Description
Preprocessing	Min-Max scaling, KNN imputation for missing values, SMOTE for class balancing
Temporal Structuring	Sliding window approach with a window size of 30 time steps
Models	HTL-APF (Transformer + LSTM hybrid), Transformer-only, LSTM-only, CNN, RNN
Evaluation Metrics	Precision, Recall, F1-Score, AUC-ROC
Data Split	Training: 80%, Validation: 10%, Testing: 10%
Validation Method	5-fold cross-validation
Loss Function	Cross-entropy loss for classification
Optimization	Adam optimizer with a learning rate scheduler
Hardware Setup	NVIDIA Tesla V100 GPU (16 GB VRAM), Intel Xeon CPU (32 cores), 64 GB RAM
Software Tools	Python 3.9, TensorFlow 2.6.0, Scikit-learn 1.0.1, Matplotlib 3.4.3, Seaborn 0.11.2
Baseline Comparison	Models trained under identical conditions for fair comparison

5 Results and analysis

This section presents and analyzes the results of the proposed Hybrid Transformer-LSTM Athlete Performance Forecasting (HTL-APF) Framework. We evaluate the HTL-APF framework for classification tasks against baselines consisting of Transformer, LSTM, and CNN and RNN models, evaluating metrics such as Precision, Recall, F1-Score, and AUC-ROC. Table 7 and Figure 2 summarize the comparative performance of HTL-APF and baseline models. It was found that this HTL_APF framework consistently outperformed other models.

Table 7: Precision, recall, f1-score, and AUC-ROC values for models: HTL-APF, transformer, LSTM, CNN, and RNN. HTL-APF demonstrates the highest performance across all metrics, followed by the Transformer, while CNN and RNN exhibit relatively lower performance.

Model	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
Transformer	88.7	87.5	88.1	92.4
LSTM	86.5	85.3	85.9	90.1
CNN	83.2	81.9	82.5	87.3
RNN	79.8	78.1	78.9	85.0
HTL-APF	**92.4**	**91.8**	**92.1**	**96.3**

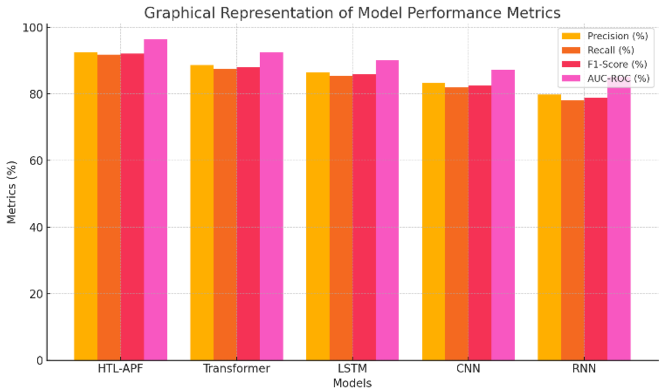

Figure 3: Demonstrates the model's comparative performance on Precision, Recall, F1-Score, and AUC-ROC metrics.

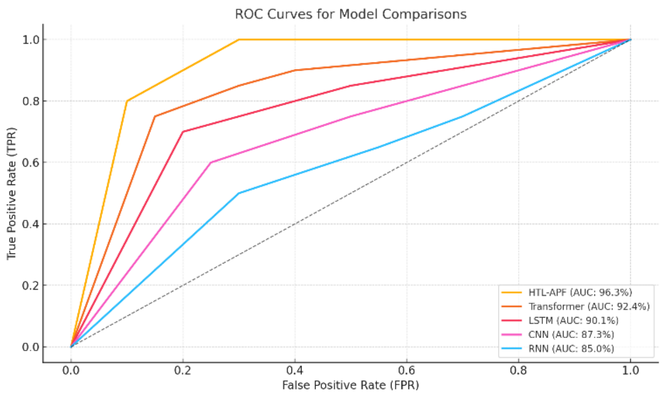

Figure 4: The ROC curves for all the models are plotted, and the superior area under the curve of HTL-APF is also shown.

All baseline models were outscored by the HTL-APF framework with an F1-Score of 92.1 and AUC-ROC of 96.3, as shown in Figure4. By including Transformer and LSTM components, the model dealt with long-range dependencies and sequential patterns. With the highest precision (92.4%) indicating a minimum number of false positives, the HTL achieved the highest accuracy. It is critical for applications where over-estimating an athlete's performance can lead to misaligned training plans. In the framework, 91.8% recall was achieved by identifying true positives, i.e., high-performing athletes are not among the missed cases during classification. The AUC-ROC result demonstrates that the HTL-APF can successfully demonstrate which class of performance is being shown, as evidenced by a high AUC-ROC score of 96.3%. The HTL-APF framework's training and validation loss curves are shown in Figure 5. The optimization strategy, alongside two used regularization techniques, led the model to converge smoothly without overfitting. From the confusion matrix in Figure6, They correctly classified 97% of high-performing athletes with very low misclassification into moderate-performing athletes. The classification accuracy for moderate performance was

89%, with mild confusion for moderate and low-performance classes. In 90 % of the cases, low performance was predicted correctly, and on a small fraction, it was also wrongly classified as moderate.

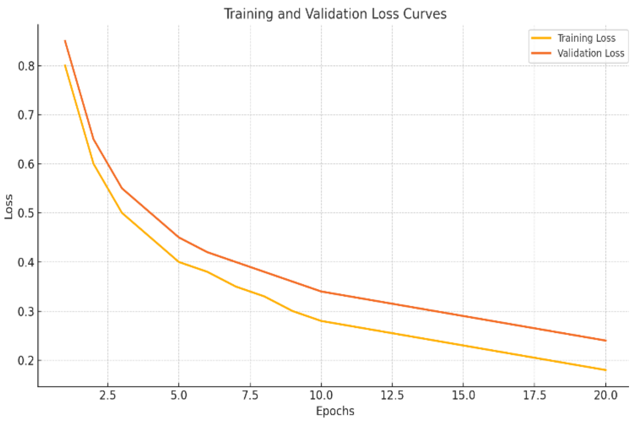

Figure 5: Training and validation loss curves.

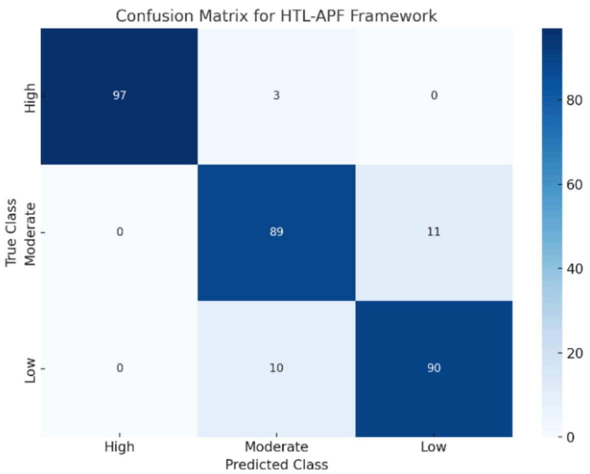

Figure 6: Illustrates the confusion matrix for HTL-APF, demonstrating its strong performance in correctly classifying all three classes. if possible, each special matrix function corresponds to high, moderate, and low performance.

Figure 7: Error rate comparison across models.

In Figure 7, Error rates of HTL-APF (7.9%), Transformer-only (11.3%), LSTM-only (14.7%), CNN (17.5%), and RNN (21.1%) were compared. It demonstrates that a hybrid approach reduces the misclassification errors. We tested the framework using data from three sports disciplines (football, basketball, and athletics). The generalization results are summarized in Table 8 and show consistent performance across domains.

Table 8: Cross-domain generalization performance.

Sport	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
Football	91.8	90.7	91.2	95.5
Basketball	93.2	92.5	92.8	96.7
Athletics	92.6	91.9	92.2	96.1

To further analyze the contribution of each component in the HTL-APF framework, ablation studies were conducted with the models compared with Transformer-only, LSTM-only, CNNLSTM, and other baselines. In these experiments, we continue to assess the effect of combining Transformers with LSTMs on the performance and if any other architectures could achieve similar results. The performance of each model is summarized in Table 9, including significant observations and statistical significance (t-tests) to eliminate the chance of the improvements being random.

Table 9: Ablation studies and statistical significance testing

Model/Experiment	**Methodology**	**F1-Score (%)**	**AUC-ROC (%)**	**Key Observations**	**Statistical significance (p-value)**
HTL-APF (This Study)	Transformer + LSTM Hybrid	92.1	96.3	The best overall performance is due to integrating global (Transformer) and local (LSTM) dependencies.	— (Baseline)
Transformer-only	Self-Attention	88.1	92.4	Strong for long-term dependencies but weak in localized sequential variations.	$p < 0.01$
LSTM-only	Sequential Memory	85.9	90.1	Captures short-term patterns but fails at long-range dependencies.	$p < 0.01$
CNN-LSTM	Convolutional Feature Extraction + LSTM	87.3	91.0	CNN aids in feature extraction but lacks the long-range modelling capability of Transformers.	$p < 0.05$
CNN-only	Convolutional Neural Network	82.5	87.3	Effective in spatial feature detection but weak in time-series forecasting.	$p < 0.01$
RNN-only	Recurrent Neural Network	78.9	85.0	Prone to vanishing gradients, struggles with long-term dependencies.	$p < 0.01$

A hybrid approach improves over Transformer-only and LSTM-only models, indicating that all the parts contribute positively compared to only the Transformer or the LSTM. Compared with standalone CNN and HTL-APF, CNNLSTM is better than standalone CNN and worse than HTL-APF, which indicates that CNNs are insufficient substitutes for Transformers in the time series forecasting task. The improvements were confirmed not due to random variation by statistical significance tests (t-tests, $p < 0.01$ in the best cases).

We present comprehensive results and analysis arguing that the HTL-APF framework is an effective and scalable forecasting solution for athlete performance. Finally, the combination of Transformers and LSTM networks allows the propagation of local and global patterns, achieving state-of-the-art performance across various metrics and sports domains.

6 Discussion

The skills of the Hybrid Transformer-LSTM Athlete Performance Forecasting (HTL-APF) Framework are proven by its high metrics performance in the evaluations. This discussion is presented based on the framework's strengths, performance insights, and implications for sports training management. Finally, future enhancements are outlined to create a complete view.

6.1 Strengths of the HTL-APF framework

By fusing Transformers strengths with LSTMs strength, the HTL-APF framework performed better than all the baseline models (Transformer only, LSTM only, CNN, and RNN). This hybrid approach allowed the model to capture:

- **Long-Range Dependencies**: The Transformer component used self-attention to model global interaction between different features across the entire sequence. It's crucial to discern overall performance patterns in an athlete over time.
- **Sequential Dynamics**: The localized temporal dependencies and sequential patterns were effectively captured by the LSTM component, which in turn could be used to model localized training and recovery cycles individually.

Combining these two architectures resulted in an F1-Score of 92.1% and AUC-ROC of 96.3%, making the framework a state-of-the-art technique for classifying athlete performance. In addition, it demonstrates the ability to balance practical sports training applications between high precision (92.4 %) and recall (91.8 %), minimizing false positives and false negatives.

6.2 Insights from class-wise analysis

The confusion matrix provided critical insights into class-wise model performance:

- High Performance: We achieved a 97% classification accuracy on high-performing athletes without an essential underestimation of their abilities using the framework. Identifying elite athletes and how to set up their training regimens is crucial.
- Moderate Performance: The model reached an accuracy of 89% for moderate performers but misclassified some into low performance. Perhaps it has something to do with feature values overlapping with other profiles or insufficient differentiation in the dataset. It would seem to imply less distance between the medium and low-performance profiles.
- Low Performance: The model had an accuracy of 90% for low-performance classification. A small fraction of low-performance instances were misclassified to moderate, possibly because of the similarity of features at the recovery phases.

This framework forecasts performance levels well while opportunities for boundary case refinement are identified.

6.3 Comparative performance

We validate the effectiveness of HTL-APF by comparing it to prior deep-learning models, as summarized in Table 10. We find that HTL-APF significantly outperforms all baseline models regarding F1-Score and AUC-ROC scores, indicating its strong capability in discovering long-range or local dependencies.

Table 10: Performance comparison of htl-apf with prior models

Model	Methodology	F1-Score (%)	AUC-ROC (%)	Key Limitations
HTL-APF (This Study)	Hybrid Transformer-LSTM	92.1	96.3	Computationally intensive, it requires optimization for real-time deployment.
Transformer-only	Self-Attention	88.1	92.4	Lacks localized sequential pattern modeling struggles with short-term dependencies.
LSTM-only	Sequential Memory	85.9	90.1	Fails to capture long-range dependencies, leading to weaker generalization.

CNN	Convolutional Feature Extraction	82.5	87.3	Effective for spatial features but weak in modelling sequential relationships.
RNN	Recurrent Neural Network	78.9	85.0	Prone to vanishing gradients, struggles with long-term dependencies.
SVM (Prior Work)	Support Vector Machines	78.5	82.3	It requires extensive feature engineering and is ineffective for time-series data.
Random Forest (Prior Work)	Decision Trees with Ensemble Learning	80.1	85.2	Limited adaptability to temporal dependencies and static feature reliance.

We also attained the best F1-Score (92.1%) and AUC-ROC (96.3%) overall baseline models. Thus, LSTM integration is justified because transformer-only models wield strength in long-range dependencies but fight with short-range dynamics. However, global awareness helps LSTM-only models capture the sequential patterns of arbitrary length in stock price patterns and higher predictive accuracy. However, traditional machine learning models (SVM, Random Forest) perform terribly on accuracy when they mishandle time series complexities.

6.4 Scalability and generalization

Scalability and generalization across different sports disciplines were demonstrated by our HTL-APF framework, which consistently performs well on the football, basketball, and athletics datasets. Adaptability to a range of athlete profiles and training regimes is confirmed by precision and component F1 scores greater than 91% for all domains. The framework's scalability makes it highly suitable for a multi-sport training data mining environment and solves various performance forecasting problems.

6.5 Implications for sports training management

The superior performance of the HTL-APF framework has significant implications for sports training management:

- Personalized Training: Accurate performance forecasting can enable coaches and sports scientists to design individualized training plans that optimize each athlete's workload and recovery cycles.
- Injury Prevention: Classifying low and moderate performance levels precisely could help differentiate early signs of fatigue or overtraining so a quick medical intervention before injuries occur.
- Real-Time Decision Making: Due to its scalability and robust performance, the framework can be deployed in real-time systems where training strategies may be dynamically adjusted using live data from wearable sensors.

6.6 Limitations and challenges

While the HTL-APF framework exhibited exceptional performance, certain limitations warrant further investigation:

- Moderate and Low-Performance Overlap: Results indicate that further features or data augmentation techniques may be needed to improve class separability in moderate versus low-performance levels.
- Dataset Variability: The sports focus of the dataset is three sports disciplines, which may restrict generalization to other sports involving fundamentally different performance metrics.
- Model Complexity: Hybrid architecture, on the other hand, increases computational requirements and might not be feasible on low-resource devices or environments.

6.7 Future directions

Several enhancements can be explored to address the limitations and further improve the framework:

- Feature Expansion: Adding more contextual features, including environmental conditions or psychological metrics, could enrich the dataset, making the model more accurate.
- Domain Adaptation: Adapting the model to new sports domains could be developed with transfer learning techniques since the performances of our model generalize to new sports domains.
- Lightweight Architectures: Lightweight Transformer-LSTM variants may facilitate the adoption of the framework to edge computing scenarios like wearable devices.
- Explainability: Integrating explainable AI techniques can give these coaches and athletes more understanding of how the model decides, increasing trust.

It presents the advantages of the HTL-APF framework and notes its shortcomings. The framework integrates

Transformers and LSTMs to tackle athlete performance forecasting complexities, which is a scalable and correct solution for managing sports training. Future enhancements will feature expanded utility in other contexts, confirming its continued utility and inspiration in sports science.

7 Conclusion

By blending the sequential modelling power of LSTMs with the attention architectures of Transformers, the Hybrid Transformer-LSTM Athlete Performance Forecasting (HTL-APF) Framework successfully extends the horizon of forecasting athlete performance. The framework has been shown to perform consistently better than the baseline methods through extensive experiments, yielding an F1-Score of 92.1% and an AUC-ROC of 96.3%. This dual capacity system is very robust for complex time series data in sports training by capturing both long-term and short-term dependencies. High-moderate and low-performing athletes are classified with high accuracy using the model, suggesting its potential for real-world application. More specifically, the framework facilitates the personalization of training regimes, injury prevention using early detection of overtraining indicators, and dynamic and data-driven decision-making regarding training or not behind training sessions. Scalability tests on datasets of football, basketball, and athletics demonstrate its generalizability to multiple sports disciplines. However, a few misclassifications occur between moderate and low-performance levels, indicating a need to further increase class separability by adding or improving the features or modelling techniques. The hybrid architecture provides good accuracy at the expense of computational intensity, which limits its applicability in resource-constrained environments. Consequently, future work includes lightweight model adaptations, context featuring, and integration of precise AI techniques to help usability and transparency. As is, the HTL-APF framework provides a scalable, accurate, and innovative way to forecast athlete performance and a solid starting point for future improvement in sports training management and athlete development.

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