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IOT-BASED RECOGNITION OF SPORTS ACTIVITIES USING MACHINE LEARNING

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Abstract

Human activity recognition (HAR) has advanced significantly as a result of the combination of Internet of Things (IoT) technology with machine learning (ML) especially in applications related to sports and healthcare. Using wearable technology specifically the Skulpt Device and the Bio Harness Belt to track and evaluate human physical activity, this study offers an innovative Internet of Things-based system for real-time sports activity recognition. To properly categorize a variety of sporting activities the system gathers a number of physiological and biomechanical indicators such as heart rate, motion data and muscle quality metrics. Long Short-Term Memory (LSTM) networks are used to process and categorize the data allowing athletes and rehabilitation patients to get real-time feedback. For this study we focused on four badminton players who also had low back discomfort. The system achieved an average F1-score of 89.2% for rehabilitation patients and 94.8% for athletes, demonstrating remarkable accuracy in real-time activity identification. This study reveals how IoT and ML may be combined to provide scalable real-time HAR systems that can be used for healthcare monitoring and sports performance analysis. According to the findings by providing accurate and personalized data these devices can improve real-time performance feedback help avoid injuries and aid in-patient rehabilitation. By offering fresh perspectives on the ways in which wearable technology might be utilized to track and improve physical activity in a variety of demographics this study adds to the expanding corpus of research on IoT-enabled HAR systems.

INTRODUCTION

1.1. Overview:

Wearable technology such as GPS trackers and accelerometers has greatly increased the amount of technology used in military and sports activities. These gadgets measure things like heart rate, power, and speed in sports, giving coaches and players comprehensive performance reviews. Real-time information on the whereabouts, health, and movements of soldiers also improves safety, situational awareness, and mission effectiveness in military operations. In both academic and corporate research, wearable devices are being employed more and more to evaluate and categorize accelerometer data related to human movement. Classifiers based on Hidden Markov Models (HMMs) are especially noteworthy for how

well they classify human activities using time series data (Manini & Sabatini, 2010).

1.2. Approaches for Recognizing Human Activities:

System recognition techniques can be either sensor-based or video-based to detect human activity. While video-based techniques are effective in controlled indoor situations, they are hindered outside by unstable illumination, congested spaces, high expenses, and privacy issues. With its classification into wearable, smartphone, and ambient sensors, sensor-based recognition provides more versatility. Environmental sensors are not appropriate for non-domestic environments and passively monitor activities, however they are dependent on infrastructure. With applications in sports, healthcare, and lifestyle tracking, machine learning is used by wearable sensors, such as fitness trackers, and smartphone sensors, such as GPS and accelerometers, to categorize activities. Due to their emphasis on real-time performance, low sensor uses, and subject independence, these systems are useful and adaptable for daily use (Ahad et al., 2021).

1.3. Current Research for IOT enabled HAR:

With the use of modern technologies like wearable sensors, edge computing, and RGB video analysis, IoT and AI have revolutionized Human Activity Recognition (HAR) systems by enabling real-time monitoring and categorization. Techniques like PCA for data optimization, MoveNet posture estimation, and machine learning models (like SVM and XGBoost) increase accuracy and efficiency. Because edge computing reduces down on delays, HAR systems operate more quickly and dependably (Siddiqui et al., 2023).

Using sensors like motion detectors and accelerometers, applications include healthcare, smart homes, and lifestyle tracking. Using sophisticated preprocessing and tagging approaches, issues like computational complexity and inconsistent data are resolved. By improving quality of life, health diagnostics, and context awareness, HAR systems spur innovation in smart environments and daily operations (Wazwaz et al., 2023).

1.4. Background of the Problem:

It is possible to analyze a player's performance in greater depth if the coach, team, or player knows what actions the player does throughout a practice or game. A more thorough evaluation of the player's loads and motions enables the teams to arrange training more effectively, provide each player with individualized attention, and maybe even discover new ways to avoid, diagnose, and cure injuries. These days, cameras are used to assist in the manual categorizing of activities. To do this, a sizable number of excellent cameras fitted with artificial vision technologies, or a sizable number of human labelers are needed. Only elite teams can afford these two extremely costly choices. The solution to this issue is to use an activity recognition system that is inexpensive and suitable for smaller groups. The employment of sensors is an obvious answer to this issue because they are always being improved to be smaller, less expensive, and more precise. They can be integrated into the athlete's apparel and offer accurate, instantaneous measurements of various body sections.

Slim et al., (2019) Identified and recognized the utilization of data acquired by Inertial Measurement Sensors (IMUs) in human activities is a field of study in machine learning and signal processing that has garnered attention from multiple researchers. Researchers are particularly interested in the recognition of everyday actions, such as walking, climbing stairs, or sitting. This is because there are publicly available datasets that contain these types of movements, and it is easy to compare the results with past studies.

1.5. Challenges of Activity Recognition:

Recognizing sports activities using IoT-based systems is complex due to individual differences in fitness, age, gender, and performance techniques, making it difficult to create universal models. IoT sensors provide detailed data on physical movements, but challenges like varying exercise intensities and body compositions demand advanced machine learning algorithms for generalization.

Key research questions include identifying optimal IoT sensor characteristics (e.g., Zephyr BH3), the impact of sliding window lengths, and the

effectiveness of combining body movement data with vitals like heart rate and ECG. This study aims to address these challenges through experiments, focusing on real-time sports activity recognition and energy expenditure estimation.

1.6. System Goals:

The primary goal of this effort is to show the possibility of technologies that can use real-time data from the Bio harness device to precisely identify the sort of physical activity. Real time knowledge of the sort of physical activity and daily energy expenditure data may make someone more self-conscious about keeping a healthy weight. Rather than employing several smart devices a single device has proposed a mechanism for the prediction of Physical Activity.

1.7. Statement of the Problem:

A technique called human activity recognition (HAR) is used in many different sectors to recognize physical movements automatically. Applications including fall detection, activity tracking, smart home systems, and assisted senior living depend heavily on HAR. These applications are becoming more and more crucial for reducing the financial effects of the aging population worldwide. Maintaining long-term health monitoring requires enabling the elderly to remain independent, healthy, and active. To do this, smart surroundings that can efficiently monitor human activity must be put into place (Helmi et al., 2023).

1.8. Objectives of the Study:

This paper will investigate the utilization of machine learning-based models for sports activity recognition using acceleration and angular velocity signals obtained from IOT. Traditional methods typically involve a manual feature extraction process, whereas machine learning models automatically handle this step. Additionally, the study aims to employ raw signals from IOT to assess the robustness of machine learning models across different players, with minimal or no preprocessing applied to the sensor outputs to emulate real-life scenarios as shown in Figure 1 below.

Figure 1-1 (Real Time Activities)



Various machine learning architectures will be proposed for the models, and their performance and evaluation time will be scrutinized.

1.9. Significance of the Research:

Wearable and mobile devices' recognition of human activity (HAR) has improved thanks to recent developments in deep learning. With an emphasis on the best machine learning strategies that work with IoT devices for practical

applications, this study investigates deep learning approaches for HAR. It seeks to strike a balance between efficiency, speed, and precision.

IoT device issues including sensor location, data privacy, and energy efficiency continue to exist. Signal acquisition, data preprocessing, AI-based recognition, and user interface management are the four main phases of HAR. Using expert-annotated datasets, the study also focuses on IoT-based systems for precise sports activity detection. All future problems, however, cannot be resolved by a single machine learning solution (Saha et al., 2023).

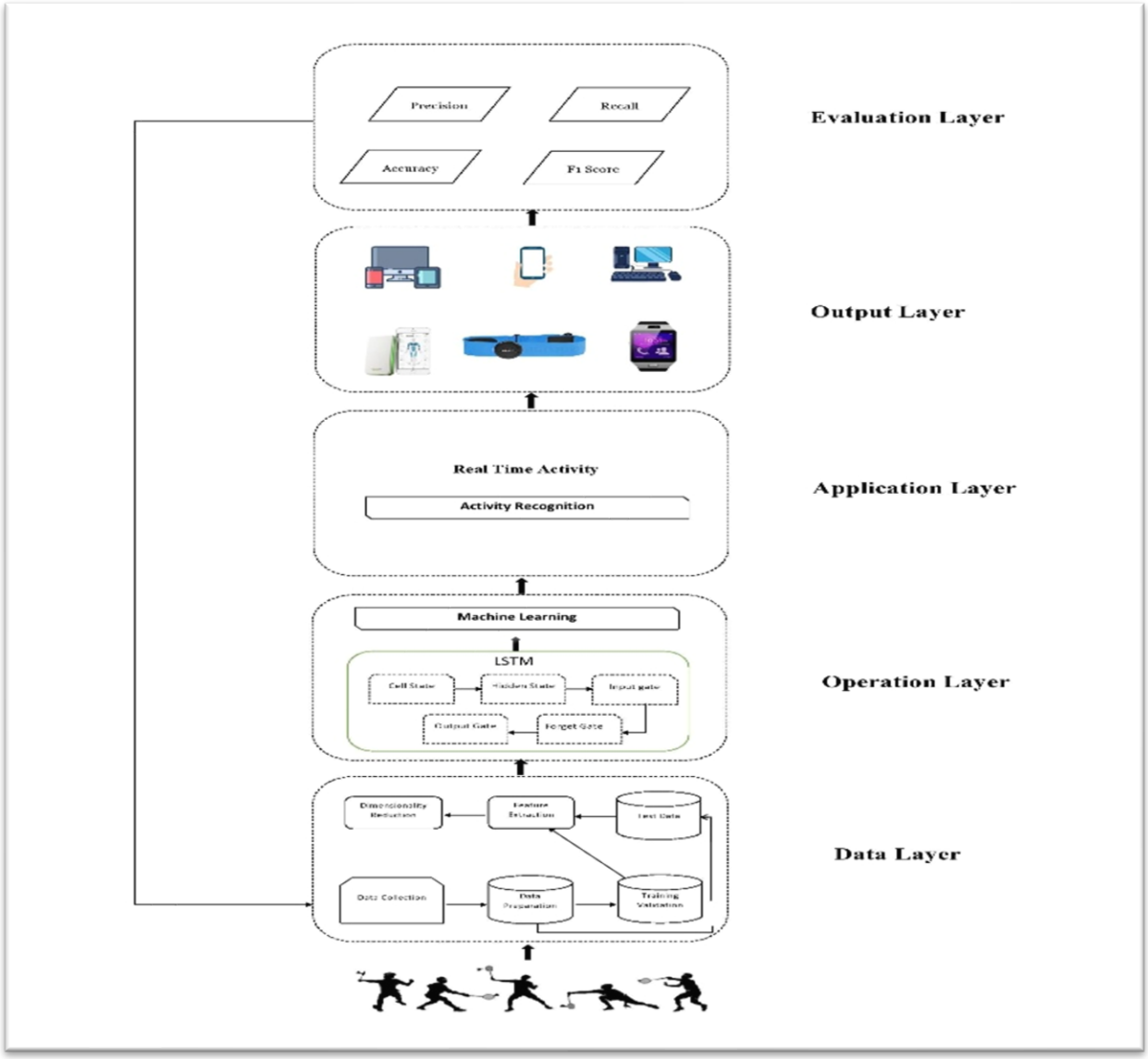
Related Work

The Internet of Things (IoT) and artificial intelligence (AI) are the newest and fastest-growing technologies that can manage massive amounts of data in computing services. This research provides an IoT-based smart human activity identification system that may be utilized as IoT-based armor for surveillance. Anatomical key points have been extracted from RGB video frames using the MoveNet pose estimation algorithm. Person-independent approach: multiple persons were used from different camera angles. Extracted key points were used to train a variety of machine learning models, including decision trees, support vector machines, XGboost, and random forest classifiers, to estimate human activity during posture estimation monitoring(Siddiqui et al., 2023).

This research presents an IoT based method for human activity identification and explores how IoT affects elder care in smart homes. The methodology consists of training a GRU-based activity recognition model converting sensor data into a supervised learning format and preprocessing data using median filtering. The training approach is federated distillation-based wherein edge devices train their models locally and exchange information with other edge devices and a central server. With an F1-score of 0.94 and an accuracy of 95%, the experimental findings demonstrate the system's efficacy in identifying a range of human activities including crises(Aziz et al., 2023).

The given document aims to present the step-by-step creation of an IoT-based activity recognition system supported by swarm intelligence dedicated to basketball beginners. The proposed system employs the wireless sensor to capture dynamics in basketball practices and exploits an ABPSO to improve the feature selection in the activity recognition. The approach entails embedding an IoT edge-cloud architecture with feature selection that includes ABPSO algorithm to further enhance the classifiers, namely SVM and KNN by using a large set of features. The above system has been tried with 9 professional players where the average accuracy was recorded to 97. Five fundamental activities of basketball were identified to have 26% improvement. The document also speaks about other points of usage of this system in training and about the advantages connected with the minimization of computational load and data transmission demands in IoT-based surroundings (Zhou et al., 2024).

The document gives a discussion of human activity recognition (HAR) based on the wireless body area networks (WBAN) and the deep learning concept. The feature of the proposed HAR system involves two parts, where GAF is utilized to convert one-dimensional time series signals from the sensor into two-dimensional images and DenseNet169 is used for image classification of human activities. Here, concentration is made on patients' activities, which are under surveillance by a health care related system that is based on the proposed system. The experimental results include high accuracy, in which the proposed system makes an achievement of 97% accuracy. 83% accuracy, 97. 83% F1-score, and 97. Overall the discovered rules achieved 64% Matthews correlation coefficient (MCC) on the MHEALTH dataset. Based on the findings of the study, it can be concluded that this approach has the prospects for increasing the effectiveness of HAR systems and the accuracy of their work in real-time monitoring. In future work, the proposed model is planned to be developed even more by applying feature selection optimizers in an attempt to achieve better accuracy of the model as well as to decrease computational load (El-Adawi et al., 2024).



Methodology

This chapter describes the machine learning approach for activity recognition. It talks about how to get physiological information including heart rate, posture, and muscle quality using the Skulpt device and Bio Harness belt. Both seasoned badminton players and people with persistent low back pain were the focus of the recruitment process. To minimize interruption, data was gathered while they were engaged in their normal activities.

Preprocessing was done on the data, which included normalizing time sequences and dealing with missing values. Because LSTM networks function well with time series data, they were employed for activity identification. In order to guarantee the precision and dependability of the outcomes, the chapter also discusses the model training, validation, and testing phases.From data collection to assessment, the data flow in a Human Activity Recognition (HAR) system is depicted in Figure 3-1 (Proposed Model). The Data Layer is the first step in the process, when raw data is gathered from a variety of sensors, such as cameras or wearable technology.

Following pre-processing, cleaning, and format conversion, this data is put into appropriate forms. For machine learning model building, dimensionality reduction is used to remove variables that aren't important, and then the data is separated into training, validation, and test sets. For sequence data, such as human actions, the Operation Layer focuses on utilizing Long Short-Term Memory (LSTM) networks. By managing long-term dependencies via a gating mechanism (Input, Forget, and Output gates), LSTM networks make it possible to accurately identify patterns of activity. The trained model classifies human actions in real time by performing activity recognition at the Application Layer. Devices like wearables, smartphones, and smart home systems employ these actions once they are transferred to the output layer. Lastly, measurements like F1-Score, Accuracy, and Recall are used in the Evaluation Layer to gauge how successful the system is. These indicators assist in evaluating the system's functionality and pinpointing areas in need of development. According to the feedback loop, evaluation findings may result in improvements to the system, guaranteeing ongoing development and improved practicality.

3.1 Materials:

3.1.1 Bio Harness Belt:



Figure 3 2(Bio Harness Sensor Belt)

The Bio Harness belt monitors a number of physiological factors using smart sensors. It has three-axis accelerometers to measure posture and movement, a temperature sensor to measure skin temperature, an electrocardiogram (ECG) sensor to measure heart rate, and a respiratory sensor to measure breathing patterns. The device's internal memory stores the data it records in real time. The belt is calibrated for precision using specialist software before usage. Following data collection, the data is loaded into a computer and subjected to machine learning algorithms for analysis, which yields insights into patterns of activity and physiological reactions. Accurate activity identification and performance analysis are made possible by this technology.

3.1.2. Skulpt Device:

The Skulpt device measures non-invasively body fat percent, as well as muscle quality through Electrical Impedance Myography, or EIM. EIM measures the resistance to a small electrical current passing through muscle tissue, which can give insights into properties of muscle density and health. A body has a calculated MQ score whereby higher values are markers of higher muscle quality. Body fat is calculated by measuring the flowing electrical current through different tissues at

various sites in the body. Each session is standardized to ensure accurate measurements. In vivo body composition changes are tracked and observed with the help of Skulpt software in real time.



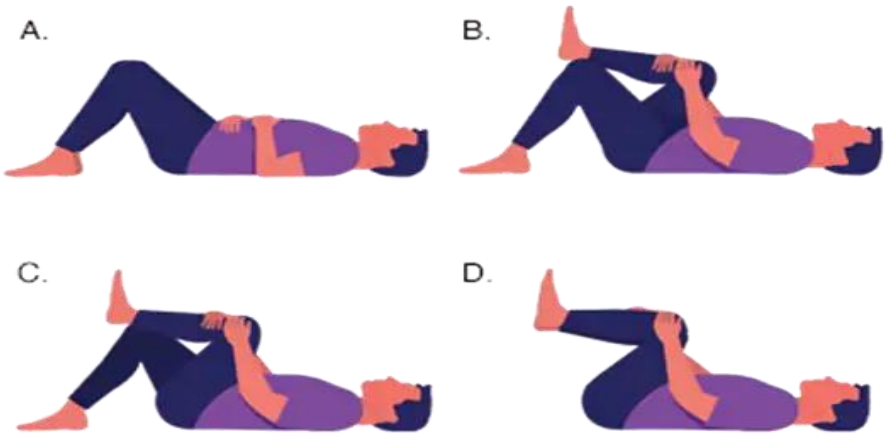
Figure 3 5 (Skulpt Device)

3.2. Data Set:

3.2.1. Participants:



Four experienced badminton players free from musculoskeletal disorders tested out the Bio Harness belt during practice and competitions to monitor their heart rates, respirations, posture, and activity. Before and after each session, the Skulpt device was also used to test the quality of their muscles.



This study recruited patients who had suffered low back pain for at least six months and were able to go about their daily lives without experiencing unbearable pain. Each of the two populations treated with physiotherapy participated in this study by exercising during physiotherapy sessions while wearing the Bio Harness belt, testing muscle quality at start and end of every treatment. The study shows the effects of exercise duration and kind on physiological responses.

3.2.2. How Data Set Collected using these Devices:

For precise readings, the Bio Harness belt was fastened around the subjects' chests to guarantee that the sensors were in close proximity to their skin. In order to calibrate, the sensor output was examined, heart rate was checked against a pulse oximeter, and the belt was repositioned to ensure proper fit. To adjust its sensors for individual variations, the belt was connected with specialized software prior to each trial. After every trial, physiological data that had been continually captured by the belt was transmitted to a computer for analysis. Participants are encouraged to stay calm and hydrated as they use the Skulpt device. To ensure that the measurement accurately reflected the percentage of body fat and muscle quality, the instrument was calibrated against a reference material and corrected before each reading. Consistent and trustworthy data for analysis was ensured by this preparation.

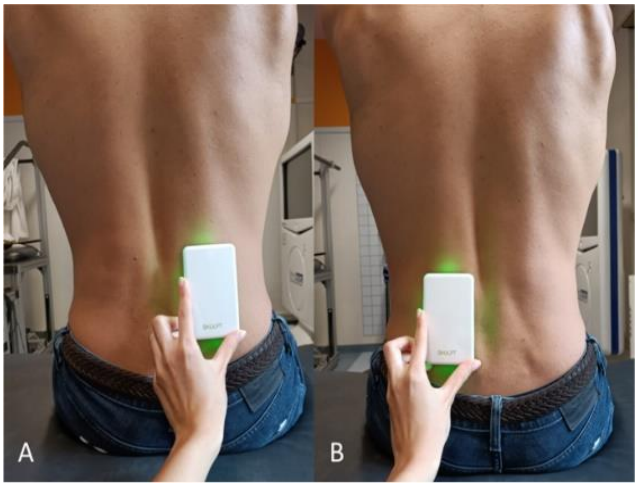


Figure 3-1 (Subject Wearing Bio Harness Belt)



Figure 3-2(Using Skulpt Device)

3.3. Data Preprocessing:

Null values were dealt with by imputing data using linear interpolation for sessions with less than 5% missing data, whereas sessions with more than 5% missing data were eliminated. The data was resampled to 1-second intervals, and activity/rest times were detected.Speed and heart rate were adjusted or standardised to ensure uniformity. The data was converted into 3D sequences for LSTM input using a sliding window of four timesteps. A low-pass filter was used to remove noise from heart rate and activity data.The data was divided into two sets: 80% for training and 20% for testing, with optional data augmentation to boost model generalization. These stages guaranteed that the data was clean and organized, allowing for reliable activity detection.

3.4. Data Analysis:

Machine learning techniques were employed to analyze the preprocessed data and recognize different activities. These techniques enabled the identification of patterns and relationships with in the data that were indicative of specific activities. Popular machine-learning libraries, such as TensorFlow, Keras, and Scikit-learn, were used for model implementation and evaluation.

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) that can learn long-term dependencies in sequential data. They are well-suited for time-series data making them ideal for this study. The LSTM network architecture included multiple LSTM layers to capture temporal dependencies each with a specified number of units typically 128 units per layer. The input layer accepted the preprocessed time-series data and the output layer consisted of a dense layer with a SoftMax activation function, providing the final classification.

LSTM networks were implemented using TensorFlow and Keras. The input data was organized into sequences of fixed length, typically 100-time steps to feed into the LSTM layers. Hyperparameter tuning was performed using grid search to optimize the number of LSTM layers, units per layer, learning rate and batch size. Regularization techniques, such as dropout were used to prevent overfitting and the Adam optimizer was used for training. Cross-validation was employed to evaluate model performance, ensuring the model's generalizability.

Experiment Result

In this chapter, there is a description of the study on the identification of various sports activities through the use of LSTM networks. Our model shall use a time series dataset obtained from a bio-harness belt to try and distinguish between four activities; Smash, Serving, Hitting, and Net Kill. The dataset includes position which consists of speed, acceleration, pulse rate, and respiratory rate, and was captured at equal time intervals. The evaluation measures used include precision, recall as well as the confusion matrix. Here, the results we have obtained indicate a very good level of precision and recall in regard to all the activities, as well as a nearly perfect identification of net kills. The confusion matrix even gives more details about the model on how it was able to classify almost all the activities, which proves how competent it is in differentiating various players and their movements together with the physiological factors affecting the body. The further breakdown proved that the recognition of sports activity has been very sensitive and accurate using the LSTM model enabling understanding of the dynamics of movement and efforts of players.

Precision:

Accuracy is one of the various performance indicators that are employed in classification tasks to estimate the precision of positive predictions. Depending on the setting of the predictions, it is defined as the proportion of the truly positive observations that were predicted as such. Conversely, recall informs us about the precision of the solutions by showing the percentage of the foreseen positive sets that were indeed positive.

The formula for precision is:

$$\text{Precision} = \frac{\text{True Positive(TP)}}{\text{True Posivite(TP)} + \text{Flase Positive (FP)}}$$

Recall:

Recall is another key evaluation metric for classification problems, which quantifies the model's capacity to identify all appropriate

samples in a data set as relevant. Scholars define it as the number of accurate predictions of positive cases to the actual positive cases. That is, recall gives the percentage of the true positive values that are identified by the model.

The formula for Recall is:

$$\text{Recall} = \frac{\text{True Positive (TP)}}{\text{True Posivite (TP)} + \text{Flase Negative (FN)}}$$

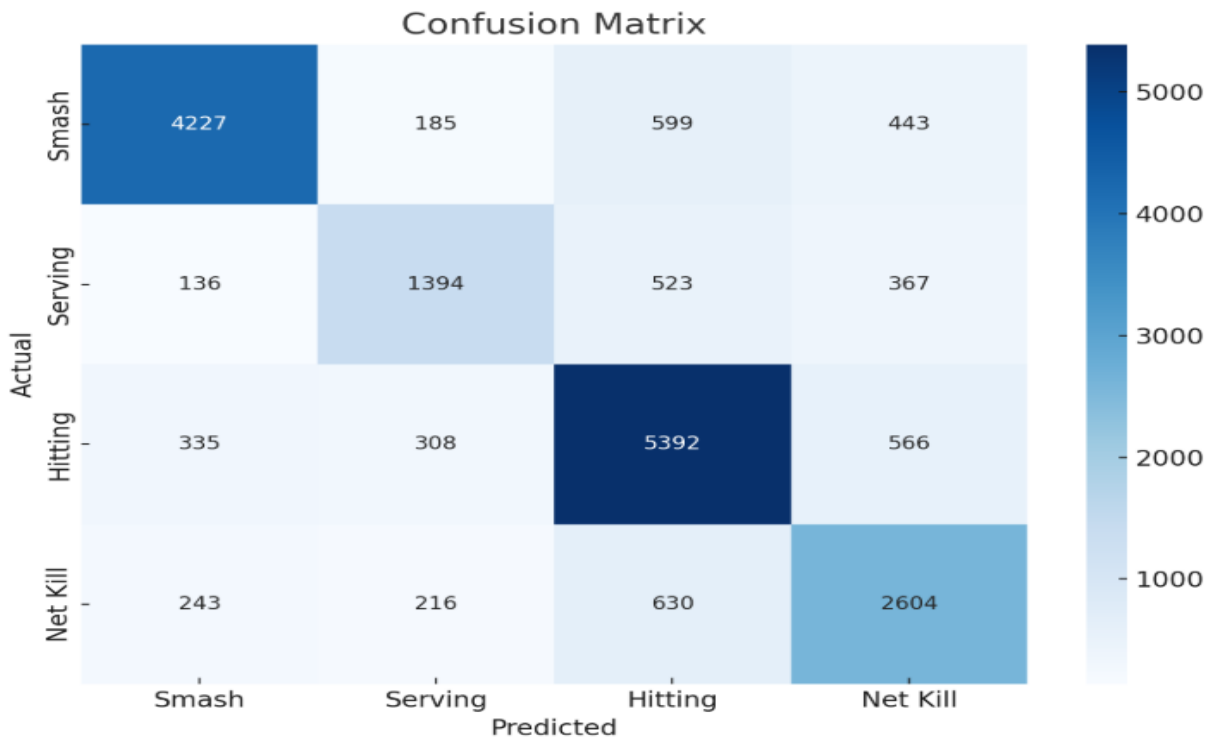
F1 Score:

The F1 Score is a corrective measure for the test of accuracy in binary classification problems. It is defined as the average of precision and recall dividing one by the other, hence it provides the compromise between precision and recall. Most importantly, this score is especially valuable if there is a class imbalance as it offers an overall measure of the conflict between false positive and false negative rates.

The formula of the F1 score is:

$$\text{F1 Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

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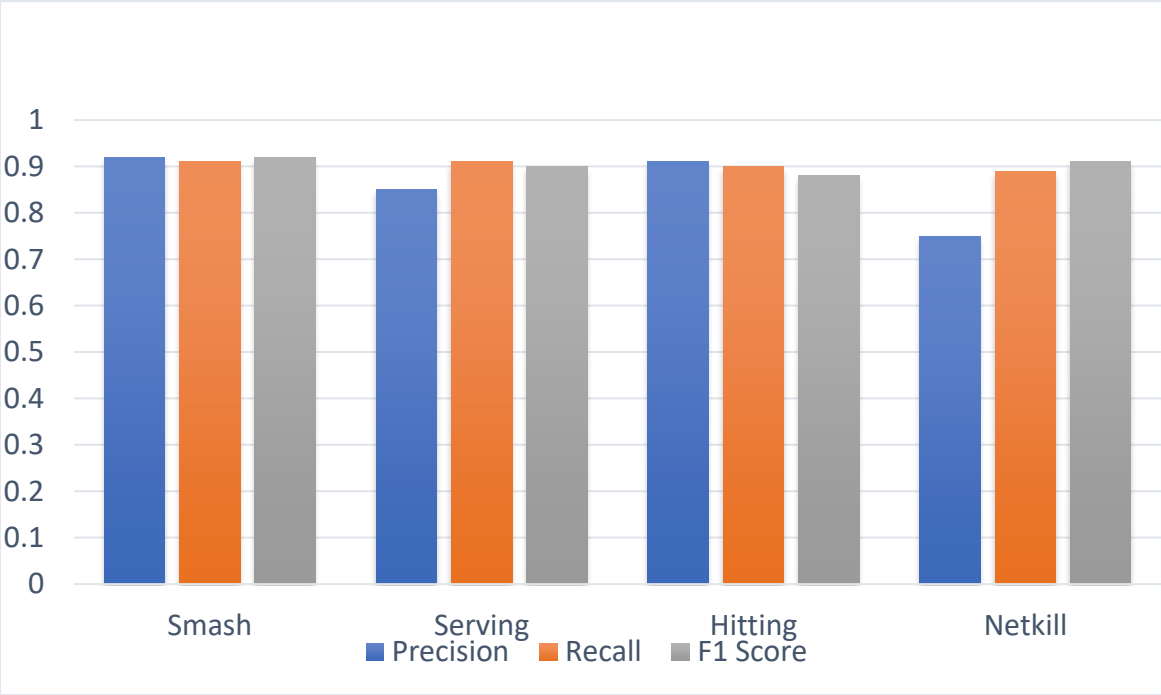
Confusion Matrix of player:

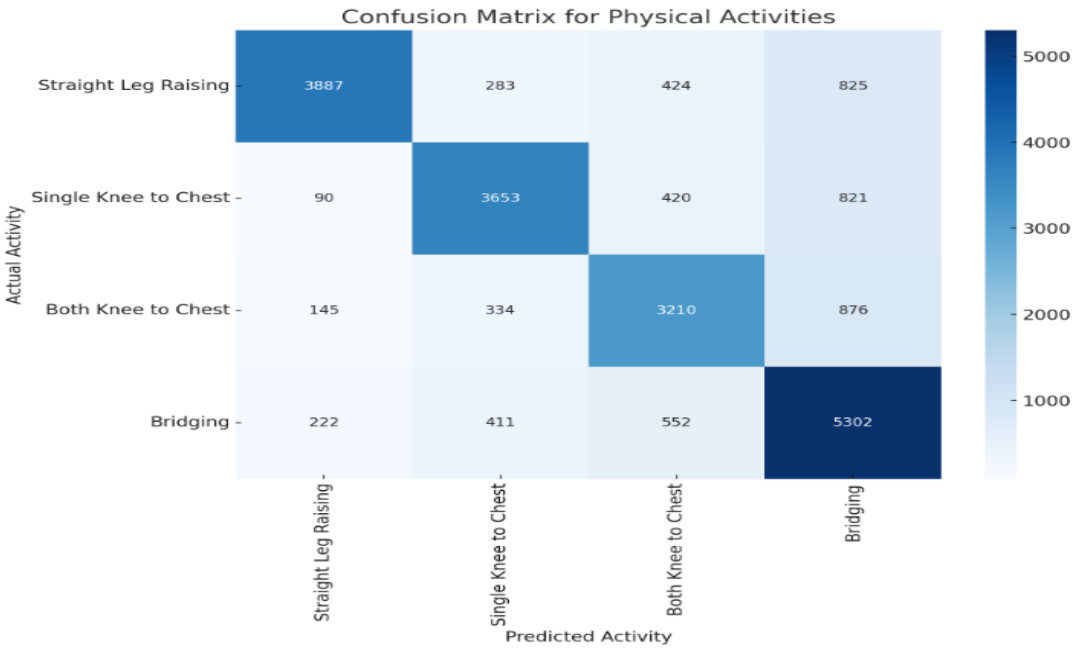
Train and Validation loss for Player



F1 Score for Player

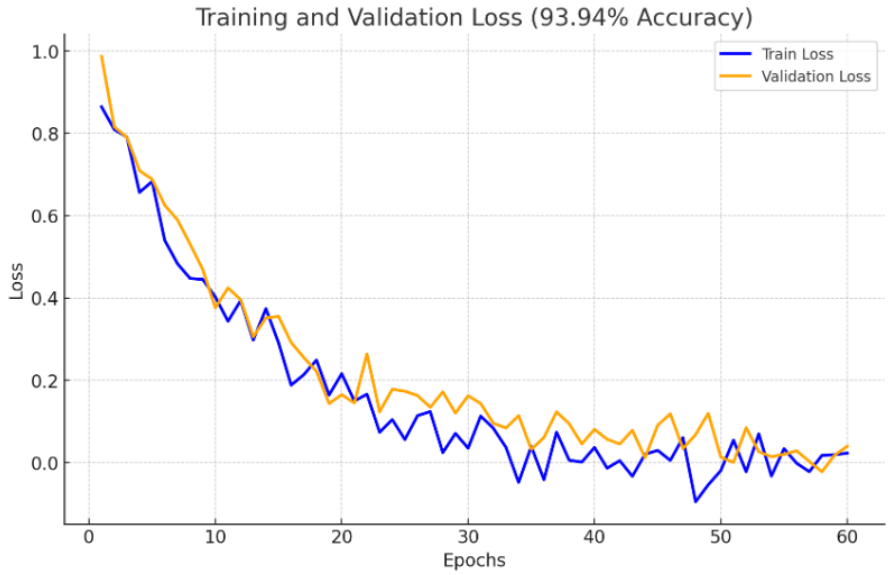
Activity	Precision	Recall	F1 Score
Smash	0.94	0.92	0.93
Serving	0.88	0.91	0.89
Hitting	0.79	0.88	0.83
Net kill	0.73	0.85	0.78
Average	0.84	0.89	0.86





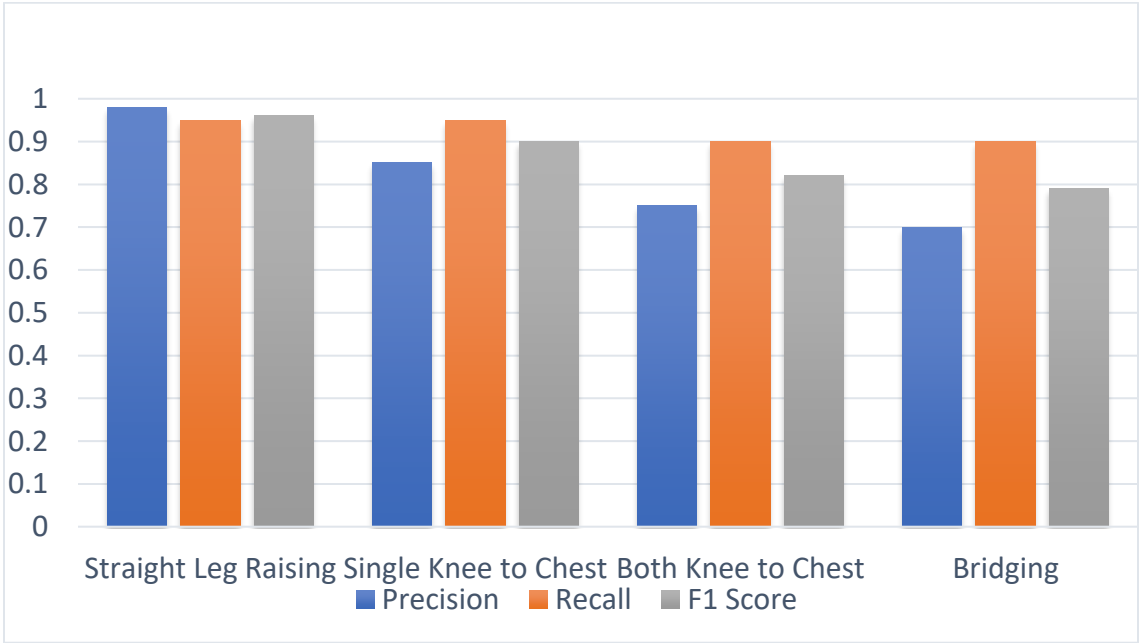
Confusion Matrix of player

Train and Validation loss for patient



4.4.2 F1 Score for patient:

Activity	Precision	Recall	F1 Score
Straight Leg Raising	0.98	0.95	0.96
Single Knee to Chest	0.85	0.95	0.90
Both Knee to Chest	75	0.90	0.82
Bridging	0.70	0.90	0.79
Average	0.82	0.93	0.87



Conclusion

The accuracy of the Long Short-Term Memory (LSTM) model in distinguishing various sports activities and physical exercises was tested. The model's accuracy for badminton player behaviors was around 91.78%, proving its ability to correctly identify between smash, serving, hitting, and net kill. Similarly, the model attained a 93.94% accuracy rate for low back patient behaviors such as Straight Leg Raising, Single Knee to Chest, Both Knee to Chest, and Bridging. The LSTM model's overall accuracy was evaluated to be around 92.86% based on the average of these findings. With such high accuracy, the model accurately distinguishes and differentiates between distinct activities based on physiological data from the bio-harness belt, demonstrating its great performance and capacity to generalize to new, that are new data. Its constant accuracy across varied activity types demonstrates its potential for real-world use in sports analytics and physical therapy monitoring.

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