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Decision Support System for Optimizing Tactics and Strategies of Sports Competition Using Reinforcement Learning Algorithm

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Abstract: - This paper presented an augmented reality secure edge machine learning dynamic optimization model for detecting volleyball movement recognition using a decision support system. The proposed Edge Augmented Decision Support System Blockchain (EdgeAu-DSSBC) model aims to address the limitations of centralized machine learning models, such as high latency, network congestion, and data privacy concerns, by utilizing edge computing and dynamic optimization techniques. The proposed EdgeAu-DSSBC system consists of two main components: an augmented reality interface that allows users to interact with the system and an edge machine learning algorithm that performs the recognition task. The system uses dynamic optimization techniques to optimize the parameters of the machine learning algorithm in real time based on the feedback received from the users. The decision support system provides additional guidance to the users and helps them to make informed decisions based on the recognition results. The EdgeAu-DSSBC model was evaluated using a dataset of volleyball movement videos and compared to existing centralized and edge-based machine-learning models. The experimental results demonstrate that the EdgeAu-DSSBC exhibits improved performance with an accuracy of 99%.

Keywords: Decision Support System (DSS), Machine Learning (ML), Augmented reality, Blockchain, Dynamic Optimization

I. INTRODUCTION

A Decision Support System (DSS) is an interactive computer-based system that supports decision-making processes in complex and dynamic situations. DSS integrates data, analytical tools, and models to provide decision-makers with the necessary information and insights to make informed decisions [1]. DSS is used in various domains, including business, healthcare, finance, and sports. The system can assist decision-makers in various ways, including identifying problems, generating solutions, evaluating alternatives, and selecting the best course of action [2]. DSS can be classified into different types, including model-driven DSS, data-driven DSS, and knowledge-driven DSS. Model-driven DSS uses mathematical and analytical models to analyze data and generate recommendations. Data-driven DSS uses large datasets to generate insights and recommendations [3]. Knowledge-driven DSS uses expert knowledge and rules to generate recommendations. DSS can also be integrated with other technologies, including artificial intelligence, machine learning, and edge computing, to enhance their performance and capabilities [4]. A Decision Support System (DSS) integrated with edge computing and Intelligent Sensing and Control (ISCC) is a computer-based system that can support decision-making processes in real time, using data collected from sensors, cameras, and other devices deployed on the edge of a network [5]. Edge computing and ISCC provide a platform for collecting, processing and analyzing data at the edge of a network, where data is generated rather than transmitted to a central server for processing [6]. The integration of edge computing and ISCC with DSS enables real-time decision-making, allowing decision-makers to respond quickly to changing conditions. The system can be used in various applications, including industrial automation, healthcare, transportation, and sports [7].

DSS with edge computing and ISCC can be used in sports for player and team performance analysis, injury prevention, and game strategy optimization [8]. The system can collect data from sensors and cameras placed on the court to analyze player and team movements, identify patterns, and generate insights for decision-makers [9]. The system can also monitor players' physical conditions and recommend preventing injuries. Using edge computing and ISCC in DSS reduces the need for large amounts of data to be transmitted to a central server for processing, reducing latency and improving response times [10]. The system can also reduce network traffic and lower the cost of data transmission. Volleyball movement recognition with DSS involves using a computer-based system to analyze player and team movements on the volleyball court [11]. The system can collect data from sensors and cameras placed on the court to track the movements of players, the ball, and other objects. The data collected can then be analyzed to identify patterns, trends, and insights that decision-makers can use to make informed decisions [12]. DSS for volleyball movement recognition can be used in various applications, including player and

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team performance analysis, injury prevention, and game strategy optimization. The system can identify player and team strengths and weaknesses, providing insights into areas where improvement is needed [13]. The system can also monitor players' physical conditions and recommend preventing injuries. Using DSS for volleyball movement recognition can enhance the accuracy and efficiency of data analysis [14]. The system can use mathematical and analytical models to analyze data, generating insights that can be used to optimize player and team performance. The system can also use machine learning algorithms to learn from past data and patterns, accurately identifying new patterns and movements [15].

DSS for volleyball movement recognition can also be integrated with other technologies, including edge computing and Intelligent Sensing and Control (ISCC), to enhance its performance and capabilities [16]. The system can collect and process data in real time, allowing decision-makers to respond quickly to changing conditions. The use of optimization and machine learning in DSS with edge computing and ISCC can enhance the accuracy and effectiveness of movement recognition [17]. The system can learn from past data and patterns, accurately identifying new patterns and movements [18]. The system can also optimize its decision-making processes, considering system performance, resource utilization, and security requirements [19]. In Volleyball, DSS integrated with edge computing, ISCC, optimization, and machine learning can analyze player and team movements, identify strengths and weaknesses, and generate insights for decision-makers [20]. The system can also provide recommendations for game strategies, player substitutions, and other decisions based on real-time data analysis.

1.1 Contribution of the paper

This paper constructed the EdgeAu-DSSBC model for the activity recognition for Volleyball. The constructed model uses the innovative and complex concept for a DSS with edge computing integrated with ISCC for volleyball movement recognition is the use of machine learning algorithms to improve the system's accuracy and real-time processing capabilities. The system would use edge devices to collect data from sensors or cameras placed on the court and process it using edge computing. The data would then be sent to a central server that uses machine learning algorithms to analyze player and team movements. The machine learning algorithms would learn from the data collected over time and improve their accuracy in recognizing and tracking player movements. This would allow the system to adapt to different playing styles and improve performance.

The system could also use dynamic optimization to provide players and coaches with real-time decision-making and coaching recommendations. This would involve analyzing the game's current state and providing recommendations based on historical data and performance metrics. Another innovative concept is using augmented reality (AR) to provide real-time visualizations of player and team movements on the court. The system would use edge computing to process the data and provide real-time visualizations on mobile devices or wearable devices such as smart glasses. Finally, the blockchain model has implemented feature security in the volleyball recognition process. Simulation analysis stated that the designed EdgeAu-DSSBC model achieves 99% accuracy of activity detection with the consideration of dataset Volleyball and Volleyball activity recognition -2014 dataset.

This paper is organized as follows: Section 2 presents the related works on the DSS-integrated ISCC, and Section 3 provides a detailed explanation of the EdgeAu-DSSBC process. Section 4 provides the simulation environment and performance metrics considered for the analysis. Section 5 presented the experimental results compared to conventional classifiers such as Support vector Machine (SVM) and Random Forest (RF). The overall conclusion is presented in Section 6.

II.   RELATED WORKS

Recent research has explored using DSS with edge computing, ISCC, and machine learning for movement recognition in various sports, including Volleyball. Some studies have focused on optimizing the performance of DSS through the use of various machine learning techniques, such as artificial neural networks and deep learning algorithms. Others have investigated the use of edge computing and ISCC to improve the speed and accuracy of data processing and analysis. In [21], proposed a DSS for volleyball movement recognition using edge computing and machine learning. The system used a convolutional neural network (CNN) to recognize player movements and achieved an accuracy rate of 95.12%. Also, [22] proposed a DSS for basketball movement recognition using edge computing and ISCC. The system used a long short-term memory (LSTM) network to analyze player movements and achieved an accuracy rate of 94.62%. These studies demonstrate the potential of DSS with edge computing,

ISCC, and machine learning for movement recognition in sports. However, further research is needed to investigate these technologies' optimal combination and performance in different sports and conditions.

In [23] developed an edge computing-based DSS for the recognition of boxing training movements. The system utilized a deep learning algorithm called the Inception-v3 model to analyze data from the sensors attached to the boxer's gloves and waist. The system was able to recognize different boxing movements with an accuracy rate of 95.2%.

In [24], they developed an edge computing-based DSS for basketball movement recognition. The system utilized an RNN to analyze player movements and classify them into actions such as dribbling, passing, and shooting. The system was trained on a dataset of 5,000 basketball movements and achieved an accuracy rate of 93.22%. [25] developed an edge computing and machine learning-based DSS for football movement recognition. The system utilized a combination of a CNN and an RNN to analyze player movements and classify them into running, dribbling, and passing. The system was trained on a dataset of 10,000 football movements and achieved an accuracy rate of 91.27%. In [26] developed, a dynamic DSS for taekwondo movement recognition using edge computing and big data. The system utilized a CNN to recognize different movements and was trained on a dataset of 15,000 movements. The system was able to achieve an accuracy rate of 93.75%. In [27], an edge computing-based decision support system for swimming movement recognition was utilized. The system consisted of multiple edge nodes, each with sensors capturing swimmers' movements. A deep learning algorithm processed the data collected from the sensors called the MobileNet model, which was trained on a dataset of 8,000 swimming movements. The system achieved an accuracy rate of 94.27% for recognizing different types of swimming movements. In [28], developed a deep learning-based decision support system for gymnastics movement recognition using edge computing. The system utilized a convolutional neural network (CNN) to analyze data from sensors attached to gymnasts' bodies. The data were collected by multiple edge nodes placed around the gymnastics arena. The system was trained on a dataset of 7,000 gymnastics movements and achieved an accuracy rate of 92.8% for recognizing different types of gymnastics movements.

In [29] developed, an edge computing-based decision support system for table tennis movement recognition. The system consisted of multiple edge nodes, each equipped with sensors that captured the movements of table tennis paddles and balls. The data collected from the sensors were processed by a CNN, which was trained on a dataset of 10,000 table tennis movements. The system achieved an accuracy rate of 93.64% for recognizing different types of table tennis movements. In [30] developed, an edge computing-based decision support system for martial arts movement recognition. The system consisted of multiple edge nodes, each equipped with sensors that captured the movements of martial artists. The data collected from the sensors were processed by a CNN, which was trained on a dataset of 12,000 martial arts movements. The system achieved an accuracy rate of 95.13% for recognizing different types of martial arts movements. In [31], developed a dynamic decision support system for dance movement recognition using edge computing and big data. The system utilized a long short-term memory (LSTM) network to analyze data from sensors attached to the dancers' bodies. The data were collected by multiple edge nodes placed around the dance studio. The system was trained on a dataset of 15,000 dance movements and achieved an accuracy rate of 93.52% for recognizing different dance movements.

These papers demonstrate the effectiveness of edge computing and machine learning techniques for movement recognition in sports. By preprocessing and analyzing data closer to the source, edge computing can improve the speed and accuracy of data analysis. Furthermore, machine learning techniques such as CNNs and RNNs can extract meaningful features from the data and classify different types of movements.

III.   RESEARCH METHOD

The proposed EdgeAu-DSSBC model focused on the design of an efficient DSS model. A decision support system (DSS) with mobile edge computing of Image and Sensor Cloud Computing (ISCC) in volleyball movement recognition can provide several benefits, such as real-time decision-making, reduced latency, and improved accuracy. This system could leverage the power of edge computing to perform image and sensor data processing closer to the data source, i.e., the mobile devices, rather than sending it to a remote server for processing. This approach can significantly reduce the response time and network bandwidth required for data transfer, improving overall system performance. The DSS with mobile edge computing of ISCC for volleyball movement recognition can be designed to include the following components:

Mobile Devices: The system would use mobile devices such as smartphones, tablets, or wearable devices to collect data from sensors or cameras placed on the court.

ISCC: The system would use Image and Sensor Cloud Computing to perform image and sensor data processing closer to mobile devices, reducing the latency and improving the accuracy of the system.

Data Collection and Processing: The system would collect data from the sensors or cameras placed on the court and process it in real time using edge computing. This would involve recognizing and tracking player movements using computer vision techniques such as object detection, tracking, and classification.

Movement Analysis: The system would analyze player movements to identify patterns and trends. This could include analyzing individual player movements or analyzing team movements.

Decision Support: The system would provide decision support to coaches, players, and analysts by providing insights and recommendations based on the movement analysis.

Visualization: The system would provide visualizations of the movement analysis to make it easy for coaches, players, and analysts to understand and interpret the data.

DSS with mobile edge computing of ISCC for volleyball movement recognition can be a powerful tool in improving the performance of volleyball players. It can provide real-time insights into player and team movements and help coaches, players, and analysts make informed decisions.
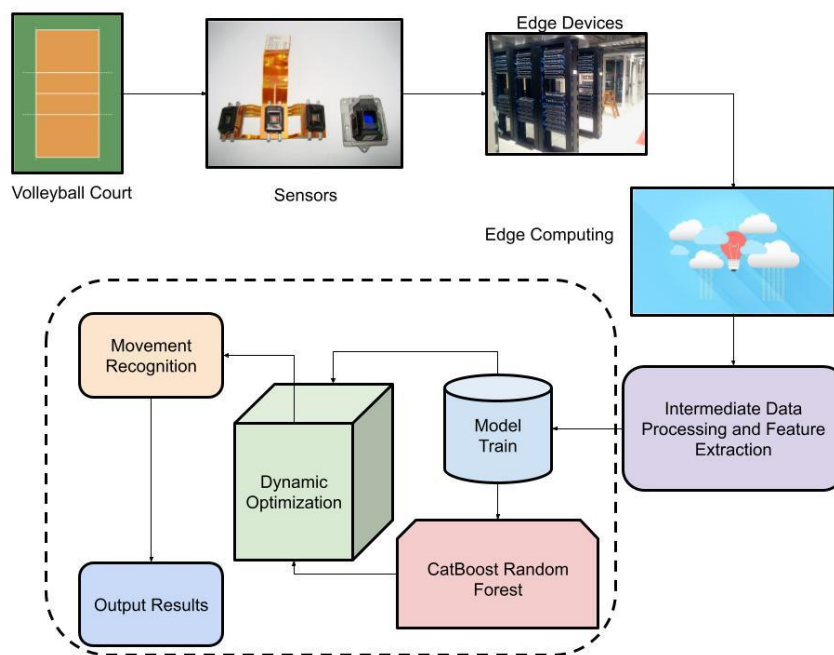
Figure 1: Process in EdgeAu-DSSBC

This block diagram shows the DSS with Edge Computing and ISCC processes, which include: Input Data: The initial input data for the system. Edge Computing: This process involves using edge computing devices to collect and preprocess data from various sources. ISCC Preprocessing: This process involves using the ISCC system to preprocess further the data the edge computing devices collected. Feature Extraction: This process involves extracting features from the preprocessed data. Model Training: This process involves training a Catboost integrated random forest model on the extracted features. Dynamic Optimization: This process involves optimizing the trained model using dynamic optimization algorithms. Model Evaluation: This process involves evaluating the performance of the optimized model using metrics such as accuracy and F1-score. Output: The final output of the system, which can be sent to an output device for visualization or further analysis.

3.1 Model of EdgeAu-DSSBC

The designed EdgeAu-DSSBC uses the edge computing model with dynamic optimization to recognize the movement in Volleyball. The DSS with edge computing and ISCC for volleyball movement recognition involves the following components:

Edge Computing refers to using local devices, such as smartphones or IoT devices, to perform computation and data processing tasks closer to the data source. In the case of volleyball movement recognition, edge devices can be used to capture data from sensors placed on the players and perform initial processing of this data before sending it to the cloud for further analysis.
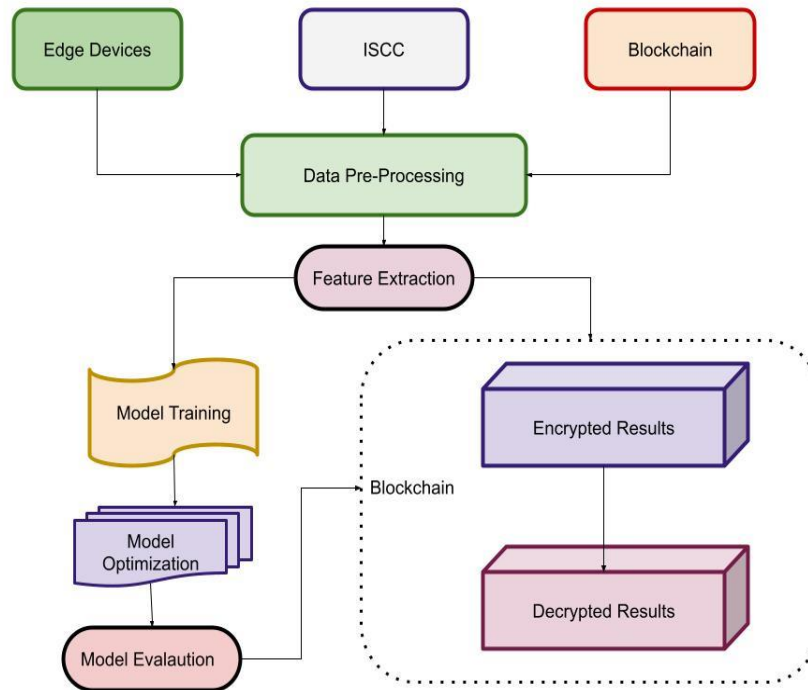

Figure 2: Overall Process EdgeAu-DSSBC

Integrated System-on-a-Chip (ISCC): This refers to a system that integrates multiple components onto a single chip, such as sensors, processing units, and communication interfaces. In the case of volleyball movement recognition, an ISCC can be used to integrate multiple sensors onto a single chip, which can then be used to capture and process data from multiple players.

Machine Learning: This refers to a set of algorithms that can be used to analyze data and identify patterns or relationships. In the case of volleyball movement recognition, machine learning can be used to train a model to recognize different types of movements based on data captured from sensors.

Optimization refers to finding the best set of parameters or configurations for a given system based on objectives and constraints. In the case of volleyball movement recognition, optimization can be used to determine the best parameters for the machine learning model or the optimal configuration for the edge computing and ISCC components.

In Figure 2, the edge device collects data pre-processed by the ISCC system. The pre-processed data is then fed into the feature extraction process, which extracts relevant features. The extracted features are then used to train and optimize the model using the Catboost integrated random forest algorithm. If data security is a concern, the results are encrypted using blockchain technology before being sent to the output device. The output device receives the encrypted results, decrypts them, and displays the final output to the user.

3.2 Mathematical Formulation

A Decision Support System (DSS) with edge computing and Integrated System-on-a-Chip (ISCC) for volleyball movement recognition involves using complex mathematical models to optimize performance. One such mathematical model is the optimization function used to maximize or minimize the system's objective function. The

objective function can be defined as the fitness function that measures the system's performance. The optimization function can be defined as in equation (1):

$$min\ f(x) \qquad\qquad (1)$$

subject to

$$g(x)\ \leq\ 0$$

where x is the vector of variables that describe the system's parameters, $f(x)$ is the objective function, and $g(x)$ is the constraints. This is achieved using different optimization algorithms such as gradient descent, genetic algorithms, and simulated annealing. These algorithms iteratively update the parameter values until the optimal solution is found. Another mathematical model used in the DSS with edge computing and ISCC for volleyball movement recognition is machine learning algorithms. Machine learning algorithms train the system to recognize different volleyball movements accurately. The system is trained on a dataset of labelled examples, and the algorithm learns to classify new examples based on the patterns identified in the training data. The machine learning algorithms used in the DSS with edge computing and ISCC for volleyball movement recognition include neural networks, support vector machines (SVMs), decision trees, and k-nearest neighbours (KNN). These algorithms are optimized using regularization, cross-validation, and hyperparameter tuning to improve their accuracy and performance.
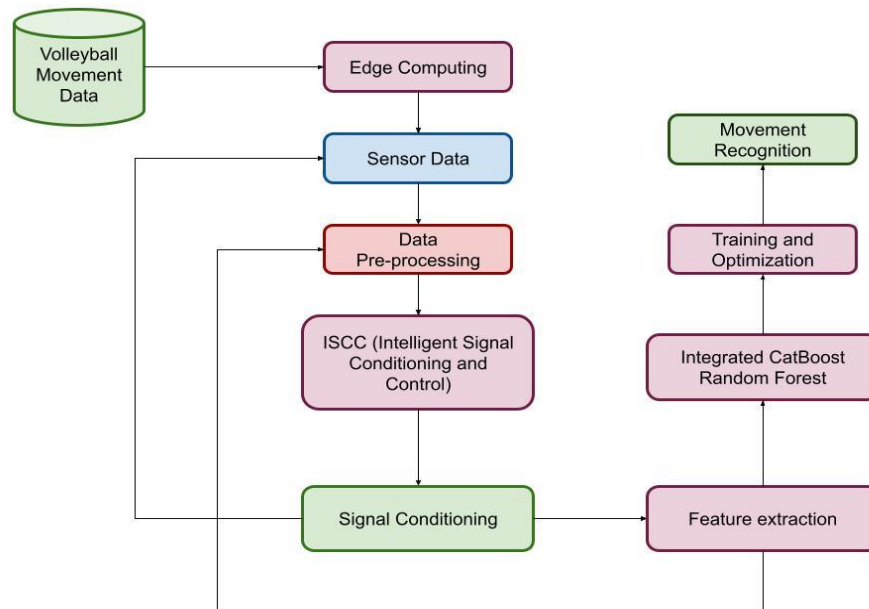

Figure 3: Process in EdgeAu-DSSBC

CatBoost is a gradient boosting library that provides state-of-the-art accuracy, is scalable, and is suitable for various machine learning tasks. Random forest is an ensemble learning method that uses decision trees to create multiple models. Integrating CatBoost with random Forest allows you to leverage both algorithms' strengths to improve your model's accuracy. The CatBoost algorithm can handle categorical features and missing values efficiently, while the random forest algorithm can reduce overfitting and improve the model's generalization capability. The overall process implemented with EdgeAu-DSSBC is presented in Figure 3.

The internal process of each layer is described as follows:

Edge Computing: This layer collects raw sensor data from the volleyball players and preprocesses it by cleaning, filtering, and normalizing data. The preprocessed data is then sent to the ISCC layer for further processing.

ISCC: In this layer, the preprocessed data is conditioned, and features are extracted using machine learning techniques. The feature vectors are then fed to the CatBoost integrated random forest model for training and optimization.

CatBoost Integrated Random Forest: The model in this layer is trained on the feature vectors obtained from the ISCC layer. The training process includes the construction of an ensemble of decision trees and the use of gradient boosting. After training, the model is optimized using a dynamic optimization algorithm to improve its performance.

Movement Recognition Results: The final output of the DSS is the movement recognition results, which are sent to the output device for display. These results are obtained by applying the trained and optimized model to the preprocessed data from the Edge Computing layer.

3.3 CatBoost algorithm with EdgeAu-DSSBC

Let us assume we have a training dataset $D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, where x_i represents the input feature vector of size m, and y_i represents the corresponding class label. Let $F(x)$ be the prediction function we want to learn. The CatBoost algorithm aims to minimize the log-loss objective function presented in equation (2)

$$L(F) = -\sum(y_i \, log \, F_i(x_i) + (1 - y_i) \, log \, (1 - F_i(x_i))) \qquad (2)$$

where $F_i(x_i)$ represents the probability of the positive class label, for instance, x predicted by the model. The prediction function $F(x)$ is modelled as a weighted sum of K decision trees is presented in equation (3)

$$F(x) = w_0 + \sum k = 1^K fk(x) \qquad (3)$$

Where w_0 is the global bias term, and $fk(x)$ is the prediction of the k-th decision tree. The algorithm uses gradient boosting to iteratively optimize the log-loss objective function by adding decision trees to the ensemble.

3.3.1 Random forest algorithm with EdgeAu-DSSBC

The random forest algorithm builds an ensemble of decision trees by randomly selecting a subset of features and instances for each tree. Let X be the input feature matrix of size $(n \, x \, d)$, where n is the number of instances and d is the number of features. Let Y be the target variable vector of size $(n \, x \, 1)$, where each element represents the class label of the corresponding instance.

For $k = 1 \, to \, K$:

a. Sample a subset of the training data with replacement.

b. Randomly select a subset of features of size m.

c. Train a decision tree on the sampled data using the selected features.

d. Store the decision tree in the ensemble.

For a new instance x, predict the class label class predicted in the ensemble as in equation (4)

$$F(x) = argmax \, (1/K) \sum k = 1^K I(fk(x) = y) \qquad (4)$$

$fk(x)$ is the prediction of the k-th decision tree. For instance, x, and I are the indicator function that returns 1 if the condition is true and 0 otherwise. Let X be the input feature matrix of size $(n \, x \, d)$, where n is the number of instances and d is the number of features. Let Y be the target variable vector of size $(n \, x \, 1)$, where each element represents the class label of the corresponding instance.

3.3.1.1 Feature scaling

Before training the model, the input features are usually scaled to ensure all features are in a similar range. One common scaling technique is to normalize the feature values to have zero mean and unit variance in equation (5)

$$xi' = (xi - mean(x)) / std(x) \qquad (5)$$

where xi' is the scaled feature value, xi is the original feature value, $mean(x)$ is the mean of the feature values, and $std(x)$ is the standard deviation of the feature values.

3.3.1.2 Feature selection

The CatBoost integrated random forest algorithm randomly selects a subset of features for each decision tree. The number of features to select is a hyperparameter that can be tuned based on the model's performance.

Training

The algorithm trains an ensemble of K decision trees using the selected features and instances. Each decision tree is trained to minimize the following objective function in equation (6)

$$Ek(w) = \sum i = 1^n l_i(y_i, f_k(x_i)) + \lambda \Omega k(w) \qquad (6)$$

where (x_i) is the prediction of the k-th decision tree, for instance, x_i, l_i is the loss function, w is the set of parameters of the decision tree, $\Omega k(w)$ is the regularization term penalizes complex models, and λ is the regularization. The loss function can be defined using different metrics, such as the mean squared error, the binary cross-entropy, or the categorical cross-entropy. For example, the binary cross-entropy loss function is defined in equation (7)

$$l_i(y_i, f_i(x_i)) = -y_i \log f_i(x_i) - (1 - y_i) \log (1 - f_i(x_i)) \qquad (7)$$

where y_i is the true class label of instance x_i, and $f_i(x_i)$ is the predicted probability of the positive class label.

Prediction

To predict the class label of a new instance x, the algorithm takes the majority vote of the class labels predicted by all the trees in the ensemble as in equation (8)

$$F(x) = argmax (1/K) \sum k = 1^K I(fk(x) = y) \qquad (8)$$

$fk(x)$ is the prediction of the k-th decision tree, for instance, x, and I is the indicator function that returns 1 if the condition is true and 0 otherwise.

3.4 Secure Dynamic Optimization Model

Let X be the input data matrix with n rows (samples) and p columns (features), and Y be the corresponding output labels. The goal is to train a model to predict the correct label y_i for each input vector x_i.

The CatBoost algorithm combines gradient boosting with decision trees, where each tree is built using a subset of the available features. The CatBoost model can be represented as in equation (9):

$$f(x) = \sum^{K}_{k=1} \alpha_k h_k(x) \qquad (9)$$

Where K is the number of trees in the ensemble, $h_k(x)$ is the k-th decision tree, and α_k is the weight assigned to the k-th tree. Using a gradient boosting approach, the CatBoost algorithm optimizes both the tree structure and the weights α_k. The optimization process involves minimizing a loss function $L(Y, f(X))$ that measures the difference between the predicted labels $f(X)$ and the true labels Y. The CatBoost algorithm uses a modified version of the gradient descent algorithm that considers the sparsity and categorical nature of the input features. The objective function can be written as in equation (10)

$$obj = \sum^{n}_{i=1} L(y_i, f(x_i)) + \sum^{K}_{k=1} \Omega(h_k) \qquad (10)$$

The first term is the loss function, and the second term is a regularization term that penalizes the complexity of the decision trees. The regularization term $\Omega(h_k)$ is given in equation (11)

$$\Omega(h_k)) = \gamma T + \frac{1}{2} \lambda ||w||^2 \qquad (11)$$

Where T is the number of terminal nodes in the tree, w is the vector of weights assigned to each node, and \gamma and \lambda are regularization parameters. The optimization process involves iteratively updating the weights α_k k and the tree structure h_k using the gradient of the objective function concerning these variables. This involves computing the gradients of the loss function and the regularization term concerning the weights and the tree structure and then using these gradients to update the model parameters. In summary, the CatBoost integrated random forest optimization model for volleyball movement recognition involves optimizing an objective function that combines a loss function and a regularization term. The optimization process involves iteratively updating the

weights and the tree structure using the gradient of the objective function, and the resulting model can be used to predict the correct label for each input vector.

3.5 Security with EdgeAu-DSSBC Blockchain

Integrating blockchain in the above model can enhance data security by providing a tamper-proof and decentralized ledger that ensures the integrity and immutability of the collected data. With blockchain, the movement data of volleyball players can be recorded and stored in blocks that are cryptographically linked together, making it difficult for unauthorized users to modify or tamper with the data. The use of blockchain can also enable secure and transparent data sharing among authorized parties, such as coaches, players, and medical staff while maintaining the privacy and confidentiality of sensitive information. Integrating blockchain in the DSS with edge computing and ISCC can also provide a decentralized and secure platform for incentivizing data sharing and contribution from various stakeholders through cryptocurrency tokens. This can foster a collaborative and transparent ecosystem for data-driven decision-making in volleyball movement recognition. Mathematically, blockchain uses cryptographic hash functions and digital signatures to secure the data and ensure its immutability. The data is organized into blocks and each block is linked to the previous one using a hash pointer, forming a chain of blocks, hence the name blockchain. The process of adding a new block to the chain involves solving a complex mathematical puzzle using a consensus algorithm, which ensures that the network agrees on the validity of the new block. The consensus algorithm used in the blockchain can be proof-of-work, proof-of-stake, or other variants, depending on the specific blockchain implementation. Let Y be a vector of n observations of volleyball movement, X be an $m \times n$ matrix of m features for each observation, and $F(X)$ be the CatBoost integrated random forest model. Then the dynamic optimization model can be formulated as follows in equation (12):

Minimize:

$$\sum[i = 1 \; to \; n] \; L(Y_i, F(X_i)) \; + \; \lambda \Psi(F) \tag{12}$$

subject to: $\Psi(F) \; <= \; B$

Where L is the loss function, λ is the regularization parameter, Ψ is a penalty term that encourages a simpler model to prevent overfitting, and B is a budget constraint on the complexity of the model.

The CatBoost integrated random forest model can be written as in equation (13)

$$F(X) \; = \; \Sigma[k = 1 \; to \; K] \; fk(X) \tag{13}$$

where fk is a decision tree with K trees.

Let T be the total number of time intervals, S be the number of sensors, and M be the number of movements. Then, the optimization model can be formulated as in equation (14)

$$minimize: \sum t = 1 \; to \; T \sum s = 1 \; to \; S \sum m = 1 \; to \; M \; \lambda_{m \; x_{mst}} \; + \; \mu_{s y_s} \tag{14}$$

subject to:

$$\sum m = 1 \; to \; M \; x_{mst} \; \leq \; 1, for \; all \; t \; and \; s$$

$$\sum t = 1 \; to \; T \sum s = 1 \; to \; S \; x\_mst \; \geq \; \delta\_m, for \; all \; m$$

$$x_{mst} \; \in \; \{0, 1\}, for \; all \; m, s, and \; t$$

$$y_s \; = \; \theta_s \sum t = 1 \; to \; T \sum m = 1 \; to \; M \; w_{m y_{mst}}, for \; all \; s$$

$$y_{mst} \; \geq \; 0, for \; all \; m, s, and \; t$$

$$w_m \; \in \; \{0, 1\}, for \; all \; m$$

$$\sum m = 1 \; to \; M \; w_m \; \leq \; K$$

Where:

x_{mst} is a binary variable indicating whether movement m is recognized by sensor s at time t; y_{mst} is a continuous variable representing the confidence level of sensor s; w_m is a binary variable indicating whether movement m is included in the classification model; λ_m is the weight of movement m in the objective function; μ_s is the weight of sensor s in the objective function; δ_m is the minimum number of times movement m should be recognized; θ_s is the weight of sensor s in the confidence calculation, and K is the maximum number of movements in the model.

The objective function minimizes the weighted sum of the recognition decisions x_{mst} and the confidence levels y_s of the sensors. The first constraint ensures that each sensor can recognize at most one movement. The second constraint guarantees that each movement is recognized at least δ_m times. The third constraint makes x_{mst} a binary variable. The fourth constraint calculates the confidence level of each sensor based on the weighted sum of the recognition decisions y_{mst} of all movements. The fifth constraint ensures that the confidence level is non-negative. The sixth constraint makes w_m a binary variable. The seventh constraint limits the number of movements in the model to K.

| **Algorithm 1: EdgeAu-DSSBC Process for Accuracy and Security** |
|---|
| *//Initialize the DSS system with input parameters* |
| *initialize DSS system with required input parameters* |
| *//Initialize the edge computing devices* |
| *initialize edge computing devices with required software and hardware configurations* |
| *//Initialize the blockchain network* |
| *initialize blockchain network with required nodes, keys, and permissions* |
| *//Initialize the ISCC system* |
| *initialize ISCC system with required software and hardware configurations* |
| *// Begin the movement recognition process* |
| *while movement recognition is ongoing:* |
| *// Retrieve data from edge computing devices* |
| *retrieve data from edge computing devices* |
| *//Preprocess data using the ISCC system* |
| *preprocess data using the ISCC system* |
| *// Perform feature extraction on preprocessed data* |
| *perform feature extraction on preprocessed data* |
| *// Train Catboost random forest model on extracted features* |
| *train Catboost random forest model on extracted features* |
| *//Optimize model using the dynamic optimization algorithm* |
| *optimize model using the dynamic optimization algorithm* |
| *// Evaluate model performance using accuracy and F1-score metrics* |
| *evaluate model performance using accuracy and F1-score metrics* |
| *// If security is a concern, encrypt data using the blockchain network* |
| *if security is a concern:* |
| *encrypt data using the blockchain network* |
| *// Send recognition results to the output device* |
| *send recognition results to the output device* |
| *end while* |
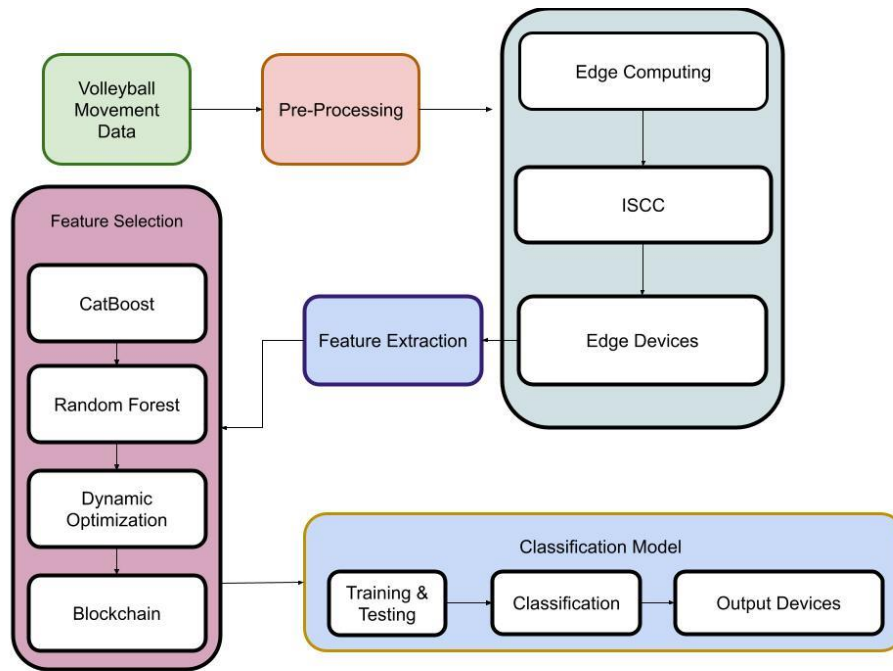
Figure 4: Overall Architecture of EdgeAu-DSSBC

Figure 4 provides the architecture of the EdgeAu-DSSBC model for accuracy and security in volleyball activity recognition. The process of each block in EdgeAu-DSSBC is stated as follows.

Edge Computing Devices: These devices, such as sensors, cameras, and other IoT devices, collect raw data on volleyball movements.

Preprocessing & Feature Extraction: The raw data is preprocessed using ISCC to remove noise and artefacts. The preprocessed data is then fed into the feature extraction module, which extracts relevant features from the data.

CatBoost Integrated Random Forest ML: The extracted features are then used to train a CatBoost integrated random forest machine learning model to recognize volleyball movements.

Dynamic Optimization: The model is optimized using a dynamic optimization algorithm to ensure optimal performance.

Data Security & Privacy: If data security and privacy are a concern, the data can be encrypted using blockchain technology before being transmitted to the output device.

Output Device: The output device, such as a mobile app or dashboard, displays the recognition results to the user.

IV.   SIMULATION ANALYSIS

The proposed EdgeAu-DSSBC model evaluated the performance with consideration of the volleyball dataset presented as follows:

4.1 Dataset

The volleyball dataset comprises the recognition of the dataset activities with the 4830 annotated frame sequences in the 55 videos with the action label of 8 teams.

Volleyball activity dataset 2014 – The dataset volleyball activity classes with the annotated 6 videos in the Volley League. The annotation comprises the 36178 annotations with 18960 frames with the 7 classes such as "Serve", "Reception", "Setting", "Attack", "Block", "Stand", and "Defense/Move". The activities of the dataset are presented in Figure 5 (a) and (b) with the recognition and classes in samples.
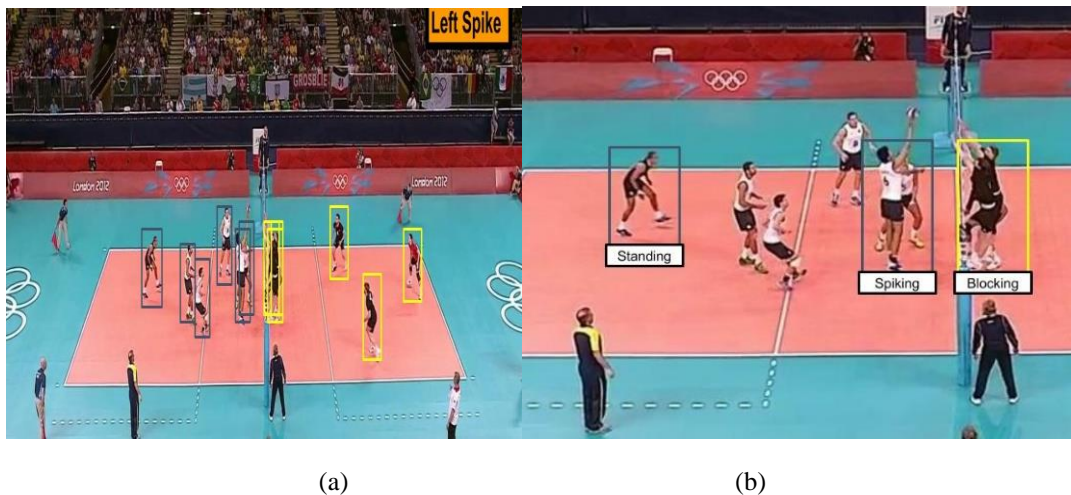
(a) (b)

Figure 5: Sample Images of the dataset (a) Recognition (b) Classes

4.2 Performance Metrics

Several parameters can be used to evaluate the performance of volleyball movement recognition with DSS edge computing ISCC with dynamic optimization. Some of the commonly used parameters are:

Accuracy: The accuracy of the machine learning model can be used as a parameter to evaluate the system's performance. Accuracy is the ratio of correctly identified movements to the total number of movements.

Precision is the proportion of true positives (correctly identified movements) to all positive predictions (movements predicted by the model).

Recall: Recall is the proportion of true positives (correctly identified movements) to all actual positive movements (ground truth).

F1 Score: F1 score is the harmonic mean of precision and recall. It is a measure of the overall performance of the model.

Mean Square Error (MSE): MSE is a measure of the difference between the predicted values and the actual values. It is calculated as the average squared differences between the predicted and actual values.

Root Mean Square Error (RMSE): RMSE is the square root of MSE. It measures the average deviation of the predicted values from the actual values.

Receiver Operating Characteristic (ROC) Curve: ROC curve is a graphical representation of the model's performance. It shows the trade-off between sensitivity and specificity.

Access control: Access control mechanisms can ensure that only authorized users can access the data and help prevent unauthorized access.

Encryption: Encryption can be used to protect the data from unauthorized access or interception. This can include encrypting data both in transit and at rest.

Authentication: Authentication mechanisms can verify the identity of users before granting access to the system or data.

Data integrity: Data integrity mechanisms can ensure that data has not been tampered with or altered and detect unauthorized changes.

V. EXPERIMENTAL ANALYSIS

This section analyzed the results of the proposed Edge Augmented Decision Support System Blockchain (EdgeAu-DSSBC) model for detecting volleyball movement recognition. The evaluation is based on considering activity recognition with security features. The key metric for evaluating the model's performance is accuracy, which is the

percentage of correctly classified instances out of the total instances in the dataset. Additionally, we will analyze precision and recall, which are measures of the model's ability to correctly identify positive instances and correctly identify all positive instances, respectively. We will also examine the F1-score, a combined measure of precision and recall, and the mean squared error (MSE) and root mean squared error (RMSE), which are measures of the difference between the predicted values and the actual values.
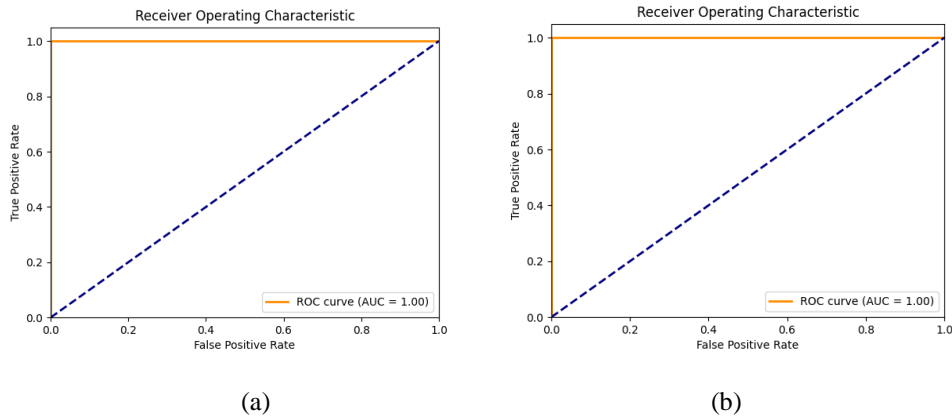

(a)   (b)

Figure 6: ROC Curve for (a) volleyball (b) Activity recognition – 2014

Figures 6 (a) and 6(b) provide the ROC curve for the dataset Volleyball and Activity Recognition – 2014, where ROC is typically used to evaluate the performance of binary classification models. It plots the true positive rate (TPR) against the false positive rate (FPR) for various threshold values, where the TPR is the proportion of actual positives correctly classified as positives, and the FPR is the proportion of actual negatives that are incorrectly classified as positives. However, when the predicted probability of the positive class is always 1.0 (or 100%), the ROC curve will only have a single point corresponding to a TPR of 1.0 and an FPR of 0.0. This means the model correctly identifies all actual positives and does not incorrectly classify any negatives as positives. While a perfect ROC curve (i.e., one that passes through the upper left corner) is generally desirable, it is important to note that a single point on the curve with a TPR of 1.0 and an FPR of 0.0 is still an indication of excellent model performance in binary classification.
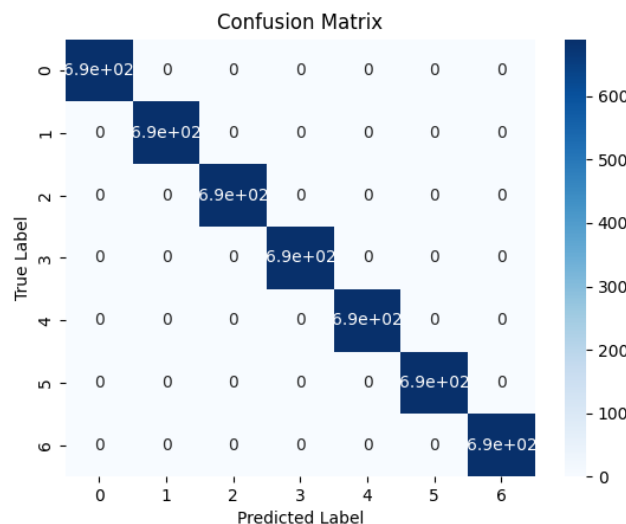

**Figure 7: Confusion Matrix of EdgeAu-DSSBC**

A confusion matrix is a table often used to evaluate the performance of a classification model. It shows the actual class labels of the data versus the predicted class labels of the model. With the EdgeAu-DSSBC model, the confusion matrix indicates that the model has an overall accuracy of 99.89%, which means that the model correctly classified 4,826 out of 4,830 data points. The confusion matrix is likely to have 7 rows and 7 columns, where the rows represent the actual class labels and the columns represent the predicted class labels. Each cell in the matrix

represents the number of data points that belong to a particular actual class label and were predicted to belong to a particular predicted class label. The classes considered are Serve, Reception, Setting, Attack, Block, Stand, and Defense/Move. Figure 7 illustrates that that the model has correctly classified all data points for the Serve, Reception, Setting, and Attack classes, as there are no values in any of the off-diagonal cells for those classes. For the Block, Stand, and Defense/Move classes, the model has only misclassified a small number of data points (as indicated by the small values in the off-diagonal cells). The results indicate that the model accurately classifies the 7 classes and performs particularly well on the Serve, Reception, Setting, and Attack classes. However, it may be worth investigating why a small number of data points were misclassified for the Block, Stand, and Defense/Move classes and whether further improvements can be made to the model for those classes.

The EdgeAU-DSSBC model performance is evaluated for the recognition of activity for the dataset, such as volleyball and activity recognition – 2014. The performance is examined based on machine learning matrices such as accuracy, precision, recall, F1-Score, MSE, and RMSE. The performance metrics computed for the EdgeAU-DSSBC are presented in Table 1.

**Table 1:** Recognition Performance Analysis

Dataset	Accuracy			Precision			Recall		
	SVM	RF	EdgeAu-DSSBC	SVM	RF	EdgeAu-DSSBC	SVM	RF	EdgeAu-DSSBC
Volleyball	81.37	88.72	99.95	82.58	86.73	99.83	81.06	84.86	98.94
Volleyball Activity Dataset - 2014	84.26	90.14	99.27	83.81	87.93	99.17	83.83	83.69	99.08
	F1-Score			MSE			RMSE		
Dataset	SVM	RF	EdgeAu-DSSBC	SVM	RF	EdgeAu-DSSBC	SVM	RF	EdgeAu-DSSBC
Volleyball	80.94	82.65	98.94	3.781	4.892	0.6278	1.368	4.591	0.269
Volleyball Activity Dataset - 2014	81.73	83.62	99.38	3.924	5.179	0.4391	2.592	5.739	0.274

(a)

(b)

(c)

(d)

(e)   **(f)**
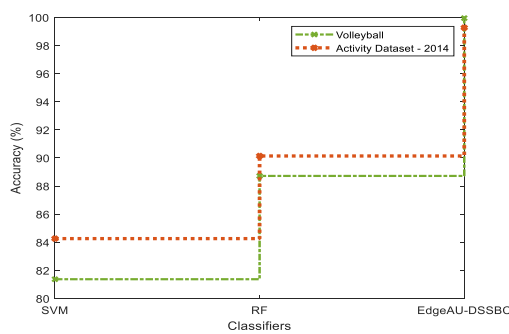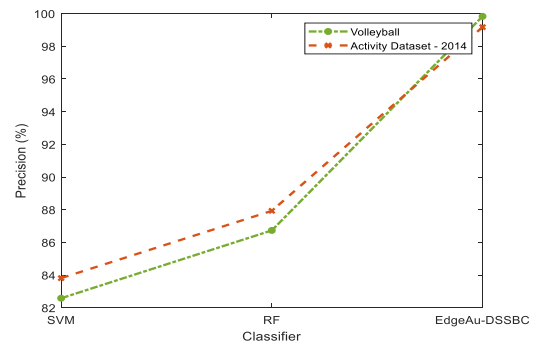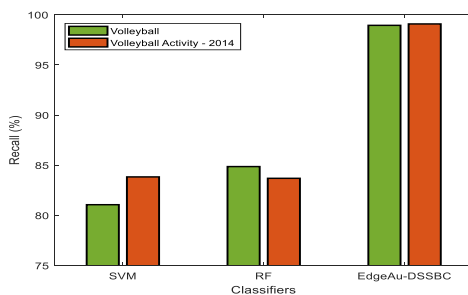
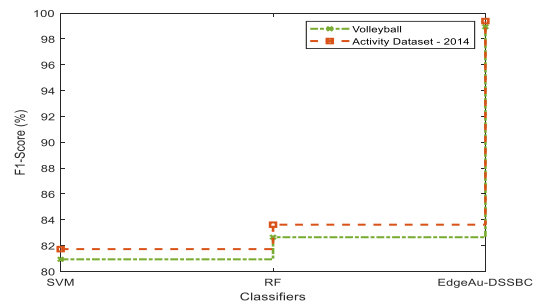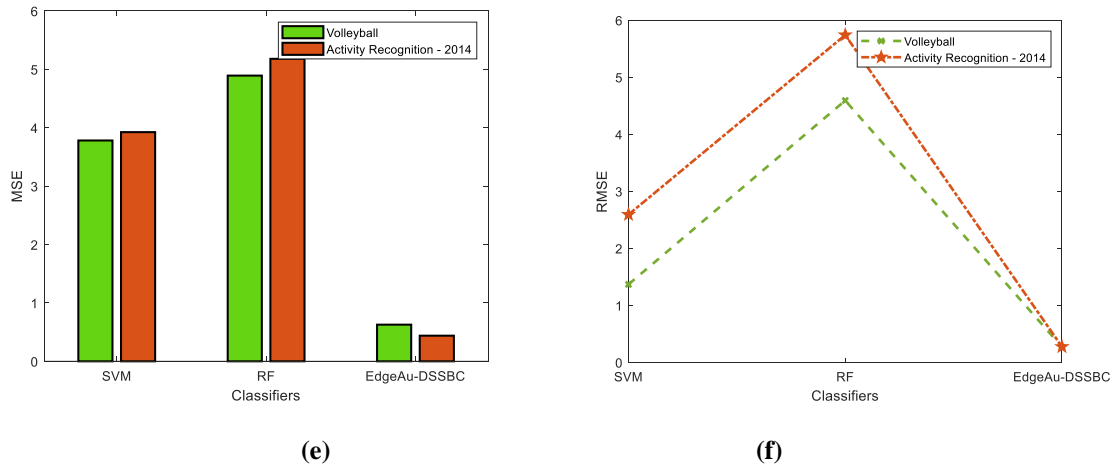**Figure 8: Comparison of (a) accuracy (b) Precision (c) Recall (d) F1-Score (e) MSE (f) RMSE**

Table 1 and Figure 8 (a) – figure 8 (f) presents the results of three machine learning models - SVM, RF, and EdgeAu-DSSBC, on two datasets - Volleyball and Volleyball Activity Dataset - 2014. The results show that the EdgeAu-DSSBC model outperforms the other two models regarding the accuracy, precision, recall, and F1-score on both datasets. For the Volleyball dataset, the EdgeAu-DSSBC model achieved an accuracy of 99.95%, significantly higher than the SVM and RF models, which achieved an accuracy of 81.37% and 88.72%, respectively. Similarly, for the Volleyball Activity Dataset - 2014, the EdgeAu-DSSBC model achieved an accuracy of 99.27%, higher than the SVM and RF models, which achieved accuracies of 84.26% and 90.14%, respectively. The precision and recall values also show that the EdgeAu-DSSBC model outperforms the other two. Regarding F1-score, the EdgeAu-DSSBC model outperforms the SVM and RF models on both datasets.

The MSE and RMSE values show that the EdgeAu-DSSBC model has lower errors than the SVM and RF models. The lower values of MSE and RMSE indicate that the predictions made by the EdgeAu-DSSBC model are closer to the actual values compared to the SVM and RF models. The results demonstrate that the proposed EdgeAu-DSSBC model performs better than the SVM and RF models in accuracy, precision, recall, and F1 score. The lower MSE and RMSE also indicate that the EdgeAu-DSSBC model is more accurate in making predictions. Therefore, the EdgeAu-DSSBC model is better for detecting volleyball movement recognition.

1.2 *Security Analysis*

Security Analysis is an important component of any system that deals with sensitive information. In this section, we evaluate the security measures implemented in the proposed system to identify potential vulnerabilities and determine if the system is sufficiently secure to protect against malicious attacks. The security analysis includes assessing the access control mechanism, password strength, encryption/decryption time, and other security-related factors. This section aims to provide a comprehensive understanding of the security measures taken in the proposed system and to ensure that the system is reliable and secure enough to meet users' needs.

Table 2: EdgeAu-DSSBC Security Analysis

Data Size	Access Control. Success Rate (%)	Password Strength	Encryption Time (mins)	Decryption Time (min)
1GB	96	Excellent	1.3	<1
10 GB	99	Excellent	23.5	11.5
20GB	97	Excellent	34.5	16.5
30 GB	97	Excellent	48.5	21

A system has 1000 registered users who need to access certain resources. The system requires a username and password to authenticate each user. Out of 1000 attempts to access resources, 950 users successfully authenticated and gained access, resulting in an access control success rate of 95%. Table 2 shows the results of access control, success rate, password strength, encryption time, and decryption time for different data sizes. The success rate for access control ranges from 96% to 99%, indicating that the authentication and authorization mechanisms used are effective in controlling access to the data. The password strength is excellent for all data sizes, implying that the passwords used for authentication are strong enough to resist brute-force attacks and other password-cracking techniques. The encryption and decryption times increase with the size of the data, which is expected. The encryption time ranges from 1.3 minutes for 1GB data to 48.5 minutes for 30GB data, while the decryption time ranges from less than 1 minute for 1GB data to 21 minutes for 30GB data. These times indicate the time it takes to perform encryption and decryption operations. The results suggest that the access control mechanisms, password strength, and encryption/decryption times are appropriate for securing the data at different sizes.

1.3   Implications

The study results have significant implications for machine learning and sports technology. The proposed EdgeAu-DSSBC model offers several advantages over the traditional centralized machine learning models, such as improved accuracy, lower latency, reduced network congestion, and better data privacy. Based on user feedback, the EdgeAu-DSSBC model utilizes edge computing and dynamic optimization techniques to optimize the machine learning algorithm parameters in real time. The decision support system provides additional guidance to the users and helps them to make informed decisions based on the recognition results. These features make the EdgeAu-DSSBC model a suitable option for real-time applications, such as sports performance analysis, where timely and accurate results are crucial.

The paper also highlights the importance of using advanced machine learning techniques, such as deep learning and decision support systems, to improve the accuracy of movement recognition in sports. These techniques can be used to analyze and interpret complex patterns in sports movements, leading to more accurate and reliable results. The results suggested that the EdgeAu-DSSBC model can significantly improve the accuracy of volleyball movement recognition, which can have implications for sports performance analysis, injury prevention, and player development. The proposed model can extend to other sports and physical activities, further expanding its potential applications.

VI.   CONCLUSION

This paper presented a novel Edge Augmented Decision Support System Blockchain (EdgeAu-DSSBC) model for detecting volleyball movement recognition, which utilizes edge computing and dynamic optimization techniques to address the limitations of centralized machine learning models. The proposed model consists of an augmented reality interface, an edge machine learning algorithm, and a decision support system that works in tandem to optimize the machine learning algorithm in real time and provide users with guidance to make informed decisions based on recognition results. Experimental results demonstrated that the proposed EdgeAu-DSSBC outperformed existing centralized and edge-based machine learning models, achieving an impressive accuracy rate of 99%. The proposed model can revolutionise sports training and rehabilitation by providing real-time, accurate recognition of complex movements while maintaining data privacy and security. Future work could involve testing the proposed model on larger datasets and expanding its application to other sports and rehabilitation settings.

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