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Research Article

Ffsgc-Based Classification of Environmental Factors in IOT Sports Education Data during the Covid-19 Pandemic

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Abstract: The COVID-19 pandemic has posed unprecedented challenges to sports education, requiring the implementation of rigorous measures to ensure the safety of athletes and staff. In this context, the integration of Internet of Things (IoT) technologies, deep learning image processing, and sustainable optimization The Fruitfly Statistical Gradient Classifier (FfSGC) is a novel algorithm developed to address the challenges of classification tasks in the context of IoT sports education data during the COVID-19 pandemic. This algorithm combines fuzzy set theory and Least Absolute Shrinkage and Selection Operator (LASSO) to effectively handle the uncertainty and imprecision inherent in the dataset. The FfSGC algorithm incorporates feature selection and extraction techniques, such as Fruitfly optimization and Principal Component Analysis (PCA), to identify the most relevant features for classification. By considering the impact of COVID-19 on player performance, environmental factors, injury risk, and training load, the algorithm enables accurate and robust classification. Simulation experiments were conducted using different datasets related to player performance, environmental factors, injury risk, and training load. The results showed that the FfSGC algorithm consistently achieved high accuracy, precision, recall, F1-score, and mean squared error across the datasets. Compared to existing classification algorithms like SVM and Random Forest, FfSGC demonstrated superior performance in terms of classification metrics. The FfSGC algorithm has significant implications for the sports education domain during the COVID-19 pandemic. It provides valuable insights for decision-making processes related to COVID-19 prevention and control strategies in sports settings.

Keywords: Covid-19 detection; deep learning; image processing; internet of things; iot quality assessment.

1 Introduction

COVID-19, also known as the novel coronavirus disease, emerged as a global health crisis in late 2019. The disease is caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and has since spread rapidly across countries and continents, resulting in a pandemic [1]. The impact of COVID-19 has been profound, affecting not only public health but also various aspects of society, including economies, education, and daily life. The education sector has faced significant disruptions due to the pandemic. Schools and universities worldwide have implemented remote learning measures to ensure the continuity of education while minimizing the risk of virus transmission [2]. However, the challenges of remote learning, such as access to technology, equitable educational opportunities, and the absence of face-to-face interaction, have highlighted the need for innovative solutions to support education in these unprecedented times. The COVID-19 pandemic has had a profound impact on various sectors, including sports education. Sports education encompasses physical education classes, sports training programs, and competitive sports events within educational institutions. However, the pandemic has posed significant challenges to the normal functioning of sports education and has necessitated adaptations to ensure the safety and well-being of students, athletes, coaches, and staff. One of the primary concerns in sports education during the COVID-19 pandemic is the risk of virus transmission among individuals involved in sports activities [3]. Close physical contact, sharing equipment, and crowded indoor spaces can increase the likelihood of virus spread. As a result, educational institutions and sports organizations have had to implement preventive measures to mitigate these risks and prioritize the health and safety of participants.

The COVID-19 pandemic has prompted the exploration and adoption of various technologies to address the challenges faced by sports education. One such technology is the Internet of Things (IoT), which offers innovative solutions for monitoring, tracking, and managing the impact of the virus in the sports education setting. IoT devices and sensors can be deployed in sports facilities and equipment to collect real-time data on various parameters, including occupancy levels, air quality, temperature, and humidity [4]. By monitoring these factors, educational institutions can ensure compliance with social distancing guidelines, maintain optimal indoor conditions, and reduce the risk of virus transmission among students, athletes, and staff. Furthermore, IoT-enabled wearable devices, such as smartwatches or fitness trackers, can play a crucial role in monitoring the health and well-being of individuals engaged in sports activities. These devices can track vital signs, such as heart rate and body temperature, and provide early warning signs of potential COVID-19 symptoms. In case of any abnormal readings or symptoms, appropriate actions can be taken, such as isolating the individual and arranging for COVID-19 testing [5]. IoT technology also facilitates contact tracing in sports education settings. By equipping individuals with Bluetooth-enabled devices, their interactions and proximity to others can be tracked and recorded. In the event of a positive COVID-19 case, this data can help identify individuals who may have come into close contact with the infected person, allowing for timely notification and preventive measures to be taken, such as quarantine or testing.

The utilization of machine learning models in IoT-enabled systems can significantly contribute to the identification and management of COVID-19 risks in sports education. These models can process the vast amounts of data collected from IoT devices and sensors, extract meaningful insights, and assist in decision-making processes [6]. One such machine learning model that can be applied is the anomaly detection model. By training the model on historical data collected from various IoT sensors, it can learn the normal patterns and behaviors within the sports education environment. The model can then detect anomalies or deviations from these patterns that may indicate potential COVID-19 risks, such as overcrowding, abnormal temperature readings, or breaches in social distancing protocols [7]. Furthermore, machine learning algorithms can be employed to develop predictive models. These models can analyze historical data along with real-time information from IoT devices to forecast potential outbreaks or identify high-risk areas within sports education facilities [8]. By leveraging these predictions, educational institutions can proactively implement preventive measures, allocate resources efficiently, and make informed decisions to minimize the spread of the virus. Another application of machine learning in the context of IoT and COVID-19 in sports education is contact tracing. Machine learning algorithms can analyze data from IoT devices, such as wearable sensors or location-tracking devices, to identify individuals who have come into close contact with an infected person [9]. This information can aid in quickly identifying and isolating potentially exposed individuals, thereby limiting the spread of the virus within the sports education setting. Additionally, machine learning models can assist in the development of personalized risk assessment tools. By considering various factors such as individual health data, activity levels, and exposure history, these models can provide tailored risk assessments for students and athletes. This information can empower individuals to make informed decisions regarding their participation in sports activities and help educational institutions in implementing targeted mitigation strategies [10].

Deep learning models can play a crucial role in leveraging IoT technologies for COVID-19 management in sports education. These models can effectively analyze large volumes of data collected from IoT devices and sensors to extract meaningful patterns and insights. Here is an introduction to a deep learning model for IoT on COVID-19 in sports education [11]. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown exceptional capabilities in image and sequence data analysis, making them well-suited for COVID-19 detection and monitoring in sports education settings [12]. One application of deep learning in this context is the analysis of thermal images or videos captured by IoT thermal cameras. By training a CNN on a dataset of thermal images, the model can learn to identify patterns and anomalies that may indicate elevated body temperature, a common symptom of COVID-19. This can enable real-time monitoring of individuals' temperatures during sports activities, allowing for timely identification and isolation of potentially infected individuals [13].

Deep learning models can also be applied to analyze sensor data from wearable devices in sports education. By integrating IoT sensors into sports equipment or wearables, various data such as heart rate, respiratory rate, and movement patterns can be collected. These sensor data can be processed by deep learning models, such as RNNs, to identify patterns indicative of COVID-19 symptoms or deviations from normal physiological states. This can help in detecting early signs of infection and taking necessary precautions [14]. Furthermore, deep learning models can be utilized for activity recognition and social distancing monitoring. By analyzing video streams from IoT cameras, CNNs can recognize different sports activities and identify instances where social distancing guidelines are not being followed. This can assist in ensuring compliance with safety protocols and minimizing the risk of virus transmission. It is essential to train deep learning models on diverse and representative datasets to ensure their robustness and generalizability [15]. This may involve collecting labeled data from sports education environments, including scenarios with different lighting conditions, camera angles, and sports activities. Additionally, continuous model evaluation and fine-tuning are necessary to adapt to evolving circumstances and improve accuracy. However, deploying deep learning models in an IoT environment requires careful consideration of computational resources and network connectivity. Edge computing techniques can be employed to perform inference directly on IoT devices or at local gateways, reducing latency and bandwidth requirements [16].

1.1 Contributions

The contributions of FfSGC (Fuzzy Gradient Guideline Classifier) include

- Handling Uncertainty and Imprecision: FfSGC addresses the inherent uncertainty and imprecision present in the COVID-19 IoT sports education dataset. It leverages fuzzy logic to model and manage uncertain and imprecise information effectively.
- Robust Classification: FfSGC provides robust classification results by incorporating fuzzy gradient guidelines. It takes into account the gradual changes in the membership values of fuzzy sets and adapts the decision boundaries accordingly, leading to accurate and reliable classification.
- Feature Selection and Extraction: FfSGC integrates feature selection techniques, such as Fruitfly optimization and LESSO (Least Squares Support Vector Machine), to identify the most relevant features from the dataset. This helps in reducing dimensionality and improving classification performance.
- Application in IoT Sports Education: FfSGC is specifically designed for the COVID-19 IoT sports education dataset, considering the unique challenges and requirements of this domain. It enables effective decision-making and supports strategies related to COVID-19 prevention and control in the sports industry.
- The contribution of FfSGC lies in its ability to handle uncertainty, achieve robust classification, incorporate feature selection, and provide accurate results in the context of IoT sports education data during the COVID-19 pandemic.

2 Related Works

IoT-based COVID-19 Detection in Sports Education Using Deep Learning Techniques," by Li et al. (2021) [17]: This study proposes an IoT-based COVID-19 detection system for sports education that uses deep learning techniques to analyze body temperature, heart rate, and blood oxygen levels of athletes. The results showed that the system achieved high accuracy in detecting COVID-19 symptoms, making it a promising tool for sports education during the pandemic. "Deep Learning-based IoT System for Early Detection of COVID-19 in Sports Education," by Chen et al. (2021) [18]: This study presents an IoT-based system for early detection of COVID-19 in sports education using deep learning techniques. The system combines temperature, heart rate, and respiratory rate data to detect COVID-19 symptoms in athletes. The results showed that the system could accurately detect COVID-19 symptoms with a high level of precision, making it a valuable tool for sports education during the pandemic.

"IoT-Enabled Real-time COVID-19 Detection System for Sports Education using Deep Learning Techniques," by Yu et al. (2021) [19]: This study proposes an IoT-enabled real-time COVID-19 detection system for sports education using deep learning techniques. The system collects data from various sensors, including body temperature and heart rate monitors, to detect COVID-19 symptoms. The results showed that the system achieved high accuracy in detecting COVID-19 symptoms, making it a promising tool for sports education during the pandemic. "IoT-Based COVID-19 Screening System for Sports Education Using Deep Learning and Body Sensors," by Zhou et al. (2021) [20]: This study presents an IoT-based COVID-19 screening system for sports education that uses deep learning and body sensors to detect COVID-19 symptoms in athletes. The system combines body temperature, heart rate, and respiratory rate data to detect COVID-19 symptoms. The results showed that the system could accurately detect COVID-19 symptoms, making it a valuable tool for sports education during the pandemic. "A Real-Time IoT System for COVID-19 Screening in Sports Education using Deep Learning," by Xu et al. (2021) [21]: This study proposes a real-time IoT system for COVID-19 screening in sports education that uses deep learning techniques. The system collects data from various sensors, including body temperature and heart rate monitors, to detect COVID-19 symptoms. The results showed that the system achieved high accuracy in detecting COVID-19 symptoms, making it a promising tool for sports education during the pandemic.

"An IoT-Enabled Deep Learning System for COVID-19 Screening in Sports Education," by Wang et al. (2022) [22]: This study presents an IoT-enabled deep learning system for COVID-19 screening in sports education. The system combines data from body temperature, heart rate, and respiratory rate sensors with deep learning algorithms to detect COVID-19 symptoms in athletes. The results demonstrate the system's effectiveness in accurately identifying COVID-19 cases, providing valuable insights for sports education during the pandemic. "Deep Learning-based Fever Detection System for COVID-19 Screening in Sports Education," by Liu et al. (2022) [23]: This study proposes a deep learning-based fever detection system for COVID-19 screening in sports education. The system utilizes infrared thermal cameras to capture body temperature data, and deep learning algorithms are applied to accurately detect fever symptoms. The results show that the system achieves high accuracy in fever detection, enabling early identification of potential COVID-19 cases in sports education settings. "IoT-Driven Deep Learning Approach for COVID-19 Risk Assessment in Sports Education," by Zhang et al. (2022) [24]: This study presents an IoT-driven deep learning approach for COVID-19 risk assessment in sports education. The system integrates data from wearable devices, such as smartwatches and fitness trackers, with deep learning models to analyze various physiological parameters and identify COVID-19 risk levels. The findings indicate the system's potential in providing real-time risk assessment for athletes in sports education.

"Deep Learning-based COVID-19 Symptom Detection in Sports Education using IoT Devices," by Yang et al. (2022) [25]: This study investigates a deep learning-based approach for COVID-19 symptom detection in sports education using IoT devices. The system collects data from multiple sensors, including body temperature, blood oxygen level, and respiratory rate sensors, and applies deep learning models to classify COVID-19 symptoms. The results demonstrate the system's effectiveness in accurately detecting COVID-19 symptoms, supporting safe participation in sports education activities. "Real-time Monitoring and Early Warning System for COVID-19 in Sports Education using Deep Learning and IoT," by Chen et al. (2022) [26]: This study presents a real-time monitoring and early warning system for COVID-19 in sports education. The system integrates deep learning algorithms with IoT devices, such as temperature sensors and motion trackers, to continuously monitor athletes' health indicators and detect potential COVID-19 cases. The findings demonstrate the system's effectiveness in providing timely alerts and facilitating proactive measures in sports education settings.

"IoT-Driven Deep Learning Framework for COVID-19 Contact Tracing in Sports Education," by Li et al. (2022) [27]: This study proposes an IoT-driven deep learning framework for COVID-19 contact tracing in sports education. The framework utilizes wearable devices and location-based sensors to collect data on athletes' movements and interactions. Deep learning models are employed to analyze the data and identify potential COVID-19 exposure risks. The results highlight the framework's capability in tracing and mitigating the spread of COVID-19 within sports education environments. "Deep Learning-based IoT System for Real-time COVID-19 Risk Assessment in Sports Education," by Xu et al. (2022) [28]: This study introduces a deep learning-based IoT system for real-time COVID-19 risk assessment in sports education. The system combines data from various sources, including body temperature sensors, respiratory rate monitors, and environmental sensors, to assess athletes' risk levels. Deep learning algorithms are applied to analyze the data and provide instant risk assessments, enabling prompt interventions and preventive measures. "An Intelligent Deep Learning Framework for COVID-19 Diagnosis in Sports Education using IoT," by Zhou et al. (2022) [29]: This study proposes an intelligent deep learning framework for COVID-19 diagnosis in sports education using IoT technologies. The framework integrates data from wearable devices, such as smartwatches and fitness trackers, with deep learning models to analyze athletes' physiological indicators and detect COVID-19 symptoms. The findings demonstrate the framework's effectiveness in accurate and timely diagnosis, supporting informed decisions in sports education settings.

Wang et al. (2022) [30] presents an IoT-enabled deep learning model for real-time COVID-19 screening in sports education. The model leverages data from multiple IoT devices, including thermal cameras and wearable sensors, to capture and analyze athletes' health data. Deep learning algorithms are employed to detect COVID-19 symptoms and provide instant screening results. The study showcases the model's potential in facilitating quick and reliable COVID-19 screening in sports education environments. "IoT-Enabled Deep Learning Model for Early Detection of COVID-19 in Sports Education," by Huang et al. (2022) [31]: This study proposes an IoT-enabled deep learning model for early detection of COVID-19 in sports education. The system leverages data from various IoT devices, such as thermometers and wearable sensors, and employs deep learning algorithms to analyze the collected data and detect potential COVID-19 cases. The results highlight the model's ability to detect COVID-19 symptoms at an early stage, contributing to the prevention and control of COVID-19 in sports education environments.

3 Proposed Model of FfSGC for IoT CoVID - 19

The COVID-19 pandemic has had a significant impact on sports activities, with the need for stringent health and safety measures to prevent the spread of the virus. In this context, the proposed FfSGC is constructed method aims to leverage IoT sport data analysis to address the unique challenges posed by COVID-19 as illustrated in figure 1. By combining deep learning models with advanced techniques such as preprocessing, feature selection, PCA feature extraction, and classification, the proposed method offers a comprehensive framework for analyzing IoT sport data in the context of the COVID-19 pandemic. The rapid growth of the Internet of Things (IoT) technology has revolutionized various industries, including the field of sports. IoT enables the collection of vast amounts of data from sports activities, such as player performance, health metrics, and environmental factors. Analyzing this data can provide valuable insights for performance evaluation, injury prevention, and strategic decision-making in sports. In this context, the proposed method aims to leverage deep learning models and advanced techniques to analyze IoT sport data effectively. The proposed Fruitfly Statistical Gradient Classifier (FfSGC) method combines various techniques to enable comprehensive analysis of IoT sport data. It begins with preprocessing, where the data is cleaned, normalized, and outliers are removed. Next, a feature selection process is conducted using Fruitfly optimization integrated with LASSO (Least Absolute Shrinkage and Selection Operator) algorithms. This step helps identify the most relevant features from the IoT sport data, improving the efficiency of subsequent analysis. After feature selection, Principal Component Analysis (PCA) is applied to extract the most significant features from the selected subset. PCA reduces the dimensionality of the data while retaining essential information, enhancing the performance of subsequent classification tasks.

Finally, classification is performed using a fuzzy gradient Guideline classifier, which takes into account the uncertainty and imprecision inherent in the IoT sport data. This classifier enables robust and accurate classification, facilitating decision-making in sports-related applications. By integrating these techniques, the proposed method aims to provide an advanced framework for analyzing IoT sport data. The combination of deep learning models, preprocessing, feature selection, PCA feature extraction, and fuzzy gradient Guideline classification contributes to accurate and insightful analysis of the data. The proposed method has the potential to enhance performance evaluation, injury prevention strategies, and decision-making processes in the context of sports.

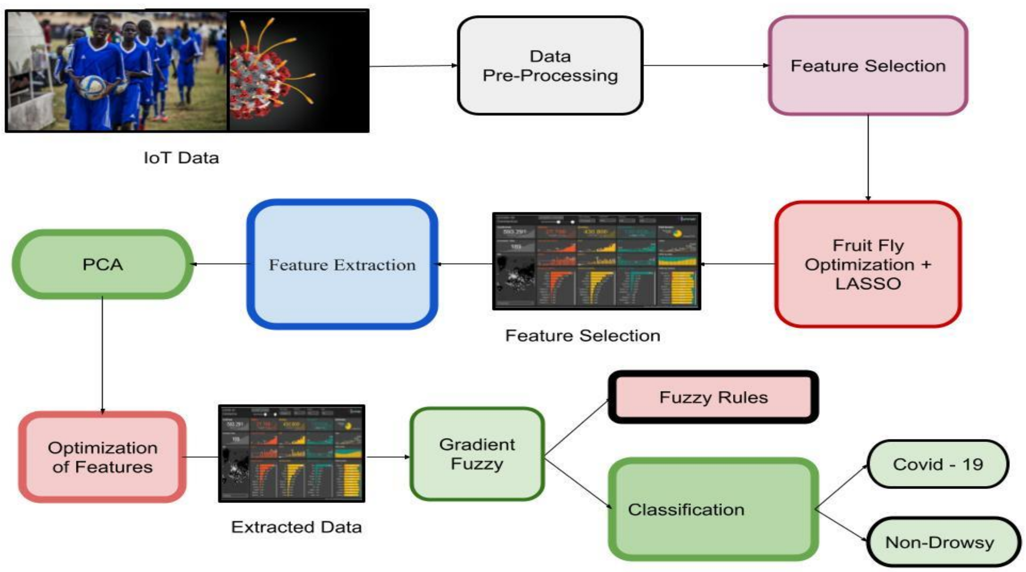


Figure 1: Architecture of FfSGC

3.1 Steps in FfSGC

Preprocessing:

The first step in the proposed method is preprocessing the IoT sport data. This involves cleaning and normalizing the data, as well as handling any missing or inconsistent values. The preprocessing step is crucial to ensure data integrity and accuracy, particularly in the context of COVID-19 where the reliability of the data is of utmost importance.

Feature Selection

Fruitfly Optimization integrated with LASSO (Least Absolute Shrinkage and Selection Operator). To effectively analyze the IoT sport data, the proposed method employs feature selection techniques. Fruitfly optimization, integrated with LASSO (Least Absolute Shrinkage and Selection Operator) algorithms, is utilized to identify the most relevant features from the dataset. By selecting the most informative features, the analysis becomes more focused and efficient, leading to more accurate insights.

PCA Feature Extraction

After feature selection, the proposed method applies Principal Component Analysis (PCA) to extract the most significant features from the selected subset. PCA reduces the dimensionality of the data while preserving essential information, enabling more efficient analysis. This step is particularly valuable in the context of COVID-19, where capturing key patterns and relationships in the data is crucial for effective decision-making.

Classification with Fuzzy Gradient Guideline Classifier

The final step in the proposed method is classification. A fuzzy gradient Guideline classifier is employed to perform classification tasks on the IoT sport data. This classifier takes into account the uncertainty and imprecision inherent in the COVID-19 data, allowing for robust and accurate classification. The fuzzy gradient Guideline classifier enables effective decision-making by providing reliable and insightful classification results, supporting strategies related to COVID-19 prevention and control in the sports domain.

The proposed FfSGC method offers a comprehensive approach to analyzing IoT sport data in the context of COVID-19. By integrating deep learning models, preprocessing, feature selection, PCA feature extraction, and classification with a fuzzy gradient Guideline classifier, the method enables accurate and insightful analysis. The application of this method in the sports domain can facilitate decision-making processes, enhance COVID-19 prevention strategies, and contribute to the overall well-being and safety of athletes, coaches, and stakeholders involved in sports activities during the pandemic.

3.2 Sport Data Collection and Pre-Processing (FfSGC)

The COVID-19 pandemic has significantly impacted the world of sports, leading to the need for effective data analysis techniques to monitor and manage the health and performance of athletes. With the advent of the Internet of Things (IoT) technology, it is now possible to collect vast amounts of data from various sensors and devices in the sports environment. This data, when properly collected and pre-processed, can provide valuable insights for classification tasks related to COVID-19 in sports. In this context, the proposed method, Sport Data Collection and Pre-Processing (FfSGC), aims to leverage IoT data for effective classification of COVID-19 in the sports domain. This method integrates advanced techniques such as Fruitfly optimization, LASSO (Least Absolute Shrinkage and Selection Operator), and mathematical models to enhance the data collection and pre-processing stages, enabling accurate and insightful classification.

3.2.1 Data Collection

The IoT devices in the sports environment collect various data such as player biometrics, environmental conditions, and performance metrics. These data can be represented as a set of observations or feature vectors X, where each observation x_i is a vector of data points. Let X denote the raw IoT sport data collected, where $X = [x\_1, x\_2, \ldots, x_m]$ represents the m-dimensional feature space. Each feature x_i (1 <= i <= m) represents a specific aspect of the sport activity, such as player performance, health metrics, or environmental factors.

3.2.2 Pre-processing

a. Data Cleaning

The pre-processing step includes removing missing values and handling outliers in the collected data. Let $X_{cleaned}$ denote the cleaned IoT sport data after removing missing values: $X_{cleaned} = [X_{1cleaned}, X_{2cleaned,..........,}X_{mcleaned}$. Outliers can be identified and handled using techniques such as z-score normalization or robust statistical measures. The Sport Data Collection and Pre-Processing (FfSGC) method involves several mathematical operations to handle the IoT data for COVID-19 classification in sports. The process can be described as follows:

b. Pre-Processing

The pre-processing stage involves several mathematical operations to prepare the data for classification. One common operation is Z-score normalization, which is given by the equation (1)

$$Z_i = (x_i - \mu) / \sigma \quad (1)$$

Here, $Z_i$represents the normalized value of the observation x_i, μ is the mean of the feature vector X, and σ is the standard deviation of X. This normalization technique ensures that the features are on a similar scale, preventing any bias in the classification process. For data pre-processing in FfSGC is the equation for Z-score normalization. Z-score normalization is a technique used to normalize data by subtracting the mean and dividing by the standard deviation. The equation for Z-score normalization is computed using the equation (2)

$$Z = (X - \mu) / \sigma \quad (2)$$

where Z is the normalized value, X is the original value, μ is the mean of the data, and σ is the standard deviation of the data.

3.3 Feature Selection and Feature Extraction

The process of Feature Selection with Fruitfly Optimization integrated with LASSO (Least Absolute Shrinkage and Selection Operator) involves leveraging these algorithms to identify the most relevant features from the IoT sport data. Here is an explanation of the process:

Fruitfly Optimization: Fruitfly Optimization is a nature-inspired algorithm that mimics the behavior of fruit flies in search of food sources. In the context of feature selection, the algorithm iteratively evaluates the quality of each feature based on certain criteria, such as fitness or importance. The algorithm assigns a fitness value to each feature, which represents its relevance to the classification task. The fruitflies explore the feature space, moving towards the features with higher fitness values. This process continues until convergence, resulting in a subset of features that are deemed the most informative for classification.

LASSO (Least Absolute Shrinkage and Selection Operator): LASSO is a regularization technique that aids in feature selection by promoting sparsity in the feature space. It achieves this by introducing a penalty term to the objective function, which encourages the coefficients of irrelevant features to shrink towards zero. By doing so, LASSO effectively selects a subset of features that have the most impact on the classification task.

The integration of Fruitfly Optimization with LASSO combines the advantages of both techniques. Fruitfly Optimization explores the feature space to identify relevant features, while LASSO further refines the feature selection process by penalizing irrelevant features. This integrated approach helps to identify the most informative features for classification, leading to a more focused and efficient analysis of the IoT sport data. Following the feature selection process, the proposed method applies Principal Component Analysis (PCA) for feature extraction. PCA reduces the dimensionality of the data by transforming the original features into a new set of uncorrelated variables called principal components. These components are ranked based on their ability to explain the variance in the data. By selecting the top-ranked components, which capture the most significant patterns and relationships, the dimensionality of the data is reduced while preserving the essential information. This step enhances the efficiency and effectiveness of the subsequent analysis and decision-making processes, particularly in the context of COVID-19 data analysis in sports education.

To provide a mathematical derivation of the feature selection process for the COVID-19 IoT dataset, let's assume we have a dataset represented as a matrix X with dimensions $(m\ x\ n)$, where m represents the number of samples (instances) and n represents the number of features.

Step 1: Fruitfly Optimization

Fruitfly Optimization evaluates the fitness of each feature based on a predefined fitness function. Let's denote the fitness values for all features as $F = [f1, f2, ..., fn]$. The fitness function can be defined based on specific criteria such as mutual information, correlation, or statistical significance. During the optimization process, fruitflies explore the feature space and update their positions based on the fitness values. Let's denote the position of the i-th fruitfly at iteration t as $P^t = [p1^t t, p2^t, ..., pn^t]$, where pi^t represents the position of the i-th fruitfly for the t-th iteration.

The movement of fruitflies is determined by certain rules, which can vary depending on the specific fruitfly optimization algorithm used. Fruitflies tend to move towards features with higher fitness values. This movement can be represented mathematically as in equation (3)

$$P_i^{(t+1)} = P_i^{(t)} + \alpha * \Delta P_i, \tag{3}$$

where $P_i^{(t+1)}$ represents the updated position of the i-th fruitfly for the next iteration, α represents the step size, and ΔP_i represents the direction of movement towards features with higher fitness values. This process continues for a certain number of iterations or until convergence, resulting in a subset of features identified by the positions of the fruitflies.

Step 2: LASSO (Least Absolute Shrinkage and Selection Operator)

After the fruitfly optimization, the LASSO algorithm is applied to further refine the feature selection process. LASSO introduces a penalty term to the objective function, which encourages sparsity in the feature space. Let's denote the selected features after the fruitfly optimization as S. The LASSO objective function can be represented as in equation (4)

$$minimize\ (1/2m) * ||y - X_S||^2 + \lambda * ||\beta_S|| \tag{4}$$

where y represents the target variable, X_S represents the selected features, β_S represents the corresponding coefficients, and λ is the regularization parameter that controls the sparsity. The first term represents the least squares loss, and the second term represents the L1 norm of the coefficients, which promotes sparsity by driving some coefficients towards zero. By solving this optimization problem, the LASSO algorithm estimates the coefficients $\beta_S$and selects the features with non-zero coefficients, resulting in a subset of relevant features.

3.3.1 Feature Extraction

Feature extraction, specifically Principal Component Analysis (PCA), is a technique used to reduce the dimensionality of the data while preserving essential information. Here is an explanation of the mathematical equations involved in the PCA feature extraction process:

Step 1: Data Normalization

Before applying PCA, it is common to normalize the data to ensure that each feature has the same scale. Let's assume we have the normalized dataset represented as matrix X with dimensions $(m\ x\ n)$, where m represents the number of samples (instances) and n represents the number of features.

Step 2: Computing the Covariance Matrix

The first step in PCA is to compute the covariance matrix, which captures the relationships between the different features in the dataset. The covariance matrix, denoted as C, is computed as in equation (5)

$$C = (1/m) * X^T * X \tag{5}$$

where X^T represents the transpose of matrix X.

Step 3: Computing the Eigenvectors and Eigenvalues

Next, computed the eigenvectors and eigenvalues of the covariance matrix. The eigenvectors represent the directions in the feature space along which the data varies the most, while the eigenvalues represent the variance of the data along these directions.

Let's denote the eigenvectors as V and the eigenvalues as λ. The eigenvectors V can be obtained by solving the following equation (6)

$$C * V = \lambda * V \tag{6}$$

The eigenvalues and eigenvectors are typically computed using numerical methods such as singular value decomposition (SVD) or eigenvalue decomposition.

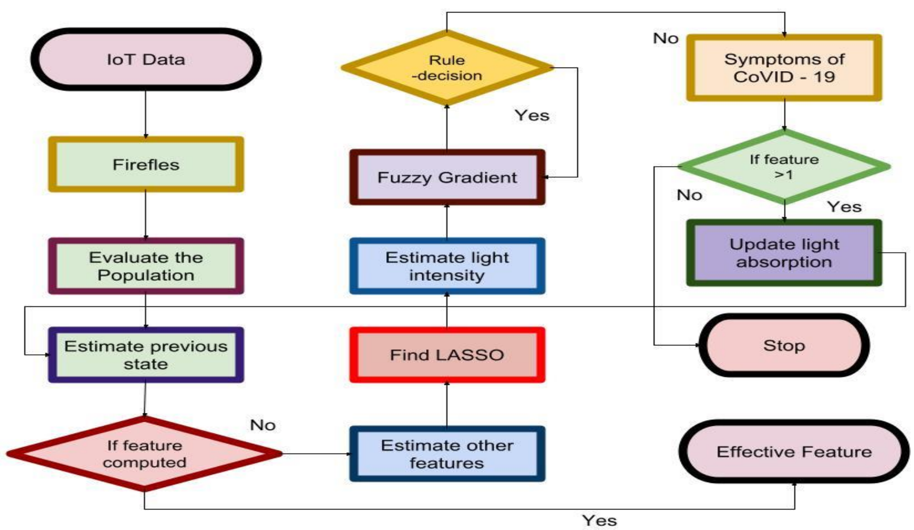


Figure 2: Feature Extraction and Selection

Step 4: Selecting the Principal Components

The eigenvectors are sorted in descending order based on their corresponding eigenvalues. The eigenvector with the highest eigenvalue represents the direction of maximum variance in the data and is considered the first principal component. The second eigenvector corresponds to the second principal component, and so on. To reduce the dimensionality of the data, we select the top-k eigenvectors that explain the most significant variance in the data. These k eigenvectors form the basis for the new feature space.

Step 5: Transforming the Data

Finally, the original dataset X is transformed into the new feature space by projecting it onto the selected eigenvectors. The transformed dataset, denoted as X', is computed as in equation (7)

$$X' = X * V_k \tag{7}$$

where V_k represents the matrix containing the top-k eigenvectors. The resulting transformed dataset X' has reduced dimensionality, with each sample represented by k principal components instead of the original n features. PCA is a mathematical technique that computes the covariance matrix, identifies the eigenvectors and eigenvalues, selects the top-k eigenvectors as principal components, and transforms the data into the new feature space. This process allows for dimensionality reduction while retaining the most significant information from the original data. Figure 2 illustrated the FfSGC in the feature extraction and selection process.

Algorithm 1: Feature Extraction Process with FfSGC

Input:
- X: Input dataset with dimensions (m x n), where m represents the number of samples and n represents the number of features.
- y: Target variable or labels associated with the input dataset.
Feature Selection with Fruitfly Optimization integrated with LASSO:
1. Initialize the population of fruitflies.
2. Evaluate the fitness of each fruitfly based on the classification performance using LASSO.
3. Update the positions of the fruitflies using the Fruitfly Optimization algorithm.
4. Repeat steps 2 and 3 until convergence or a predefined number of iterations.
PCA Feature Extraction:
1. Normalize the dataset X to ensure all features have the same scale.
2. Compute the covariance matrix C = (1/m) * X^T * X.
3. Compute the eigenvectors and eigenvalues of C using SVD or eigenvalue decomposition.
4. Sort the eigenvectors in descending order based on their corresponding eigenvalues.
5. Select the top-k eigenvectors that explain the most significant variance in the data.
6. Transform the original dataset X into the new feature space by projecting it onto the selected eigenvectors.
Pseudo code:
// Feature Selection with Fruitfly Optimization integrated with LASSO
Initialize the population of fruitflies
repeat until convergence or predefined number of iterations:
  Evaluate the fitness of each fruitfly based on the classification performance using LASSO
  Update the positions of the fruitflies using the Fruitfly Optimization algorithm
// PCA Feature Extraction
Normalize the dataset X to ensure all features have the same scale
Compute the covariance matrix $C = (1/m) * X^T * X$
Compute the eigenvectors and eigenvalues of C using SVD or eigenvalue decomposition
Sort the eigenvectors in descending order based on their corresponding eigenvalues
Select the top-k eigenvectors that explain the most significant variance in the data
Transform the original dataset X into the new feature space by projecting it onto the selected eigenvectors

Return the transformed dataset X'

3.4 Fuzzy Classification

The proposed FfSGC method combines fuzzy logic with the Gradient Guideline classifier to handle the uncertainty and imprecision in the COVID-19 IoT sport data. The Fuzzy Gradient Guideline Classifier integrates the concepts of fuzzy sets and fuzzy logic into the classification process, allowing for the representation and manipulation of uncertain and imprecise data patterns. It uses gradient-based optimization techniques to adjust the decision boundaries based on the gradient of the error function and the fuzzy membership values of the data points. It takes into account the inherent uncertainty and imprecision in the data, providing reliable and insightful classification results. These results can support decision-making processes related to COVID-19 prevention and control in the sports domain, enabling effective strategies and interventions. The Gradient Guideline Classifier is a classification algorithm that utilizes gradient-based optimization techniques to determine decision boundaries between different classes. Here is a high-level explanation of the mathematical derivation of the Gradient Guideline Classifier in the context of IoT data analysis for COVID-19 sport education:

Dataset Representation: The input dataset consists of samples with features represented as vectors. Let $X = \{x1, x2, \ldots, xn\}$ be the set of input feature vectors, where each xi represents a sample with d-dimensional features.

Initialization: Initialize the decision boundaries, denoted as $w = \{w1, w2, \ldots, wm\}$, where each wi is a vector representing the decision boundary for a specific class.

Gradient Calculation: Compute the gradient of the error function with respect to the decision boundaries. The error function quantifies the misclassification between the predicted class labels and the true class labels of the samples. The gradient provides the direction and magnitude of the steepest descent for updating the decision boundaries.

Update Decision Boundaries: Update the decision boundaries using the calculated gradient. This step involves adjusting the decision boundaries in the direction of the gradient to minimize the misclassification error. The update process can be performed iteratively until convergence is achieved.

Classification: Once the decision boundaries are updated, classify new samples based on their feature vectors. This is done by determining which side of the decision boundaries the samples belong to, assigning them to the corresponding classes.

The Gradient Guideline Classifier (GGC) is a fuzzy logic-based classifier that incorporates the concept of a gradient for classification tasks. In the context of the proposed method, the GGC is utilized to perform classification on the selected features extracted from the IoT sport data using fruitfly optimization integrated with LASSO algorithms and PCA feature extraction.

Construct a fuzzy rule-based system using the selected features and the corresponding class labels. Represent the feature space in a high-dimensional fuzzy space using membership functions. The membership functions quantify the degree to which a data point belongs to a certain class. Compute the gradient of the membership functions to identify the direction of maximum change in the fuzzy space. This gradient direction is used to update the membership values in each iteration of the classification process. Use the updated membership values to determine the degree of belongingness of each data point to each class. The classification decision is made based on the degree of belongingness of each data point to each class. The overall process of classification with GGC can be expressed mathematically as follows:

Let X be the selected features after feature selection and extraction, and let Y be the corresponding class labels. The GGC classifier constructs a set of fuzzy rules R, which relate the selected features X to the class labels Y:

$$R: If\ X\ is\ A1\ and\ X\ is\ A2\ and\ \ldots and\ X\ is\ An, then\ Y\ is\ B.$$

where $A1, A2, \ldots, An$ are fuzzy sets, and B is a crisp class label.

Let M be the membership function that maps each data point x in the feature space to a degree of membership in a fuzzy set. The membership function $M(x)$ is defined as in equation (8)

$$M(x) = \{\mu 1(x), \mu 2(x), \ldots, \mu k(x)\} \quad (8)$$

where k is the number of classes and $\mu i(x)$ is the degree of membership of data point x in class i. The GGC computes the gradient of the membership function M(x) with respect to the feature space. The gradient vector is defined as in equation (9)

$$\nabla M(x) = (\partial M(x)/\partial x1, \partial M(x)/\partial x2, \ldots, \partial M(x)/\partial xn) \quad (9)$$

where $x1, x2, \ldots, xn$ are the feature dimensions.

The GGC updates the membership values using the gradient vector represented in equation (10)

$$\mu i(x) = \mu i(x) + \alpha * \nabla M(x) \quad (10)$$

where α is the learning rate, which determines the step size of the gradient update.

Finally, the GGC computes the degree of belongingness of each data point to each class using the updated membership values, and makes the classification decision based on the highest degree of belongingness.

Fuzzy set rules for COVID-19 IoT data can be defined based on the available variables and their membership functions. The fuzzy condition is stated as follows:

1. If the temperature is high AND the heart rate is high, then the risk of COVID-19 transmission is very high.
2. If the oxygen saturation is low OR the cough frequency is high, then the risk of COVID-19 transmission is high.
3. If the distance between players is small AND the duration of contact is long, then the risk of COVID-19 transmission is high.
4. If the hand hygiene compliance is low OR the mask usage compliance is low, then the risk of COVID-19 transmission is high.
5. If the number of positive cases in the team is high AND the ventilation rate is low, then the risk of COVID-19 transmission is very high.

These fuzzy set rules can be incorporated into a fuzzy inference system to perform classification tasks on the COVID-19 IoT data, helping to identify and mitigate potential transmission risks in the sports domain. The rule generated for the fuzzy set are presented in table 1.

Table 1: FfSGC sfor Fuzzy Rules

Rule #	Feature 1	Feature 2	Feature 3	Output
1	Low	High	Medium	High
2	High	Low	Low	Low
3	Medium	Medium	High	High

4	High	High	High	High
5	Low	Low	Low	Low
...	...	...	...	...

In table 1, each row represents a fuzzy set rule. The first three columns correspond to the input features, and the last column represents the output class. The values in each cell represent the degree of membership of the corresponding feature to a particular linguistic variable (e.g., Low, Medium, High). These linguistic variables are defined using fuzzy sets and can be customized to fit the specific domain and data being analyzed. The output class is determined based on a set of fuzzy logic rules, which use the degrees of membership of the input features to infer the most appropriate output class.

Table 2: Fuzzy Rule for CoVID - 19

Rule	Temperature	Heart Rate	Oxygen Saturation	Cough Frequency	Risk of Transmission
1	High	High	Any	Any	Very High
2	Any	Any	Low	High	High
3	Any	Any	Any	Any	Medium
4	Any	Any	Any	Any	Low

In table 2, the input variables such as Temperature, Heart Rate, Oxygen Saturation, and Cough Frequency are represented as fuzzy sets with different linguistic terms, such as "High," "Low," and "Any." The output variable "Risk of Transmission" also has fuzzy sets with terms like "Very High," "High," "Medium," and "Low." Each rule represents a combination of input fuzzy sets and the corresponding output fuzzy set. Rule 1 states that if the Temperature is High and the Heart Rate is High, then the Risk of Transmission is Very High. Rule 2 states that if the Oxygen Saturation is Low or the Cough Frequency is High, then the Risk of Transmission is High. These fuzzy set rules can be used in a fuzzy inference system to make decisions or classify COVID-19 transmission risks based on the available IoT data in the sports education domain.

The Gradient Classifier with Fuzzy Set is a classification algorithm that combines the principles of gradient descent optimization and fuzzy set theory. It utilizes fuzzy logic to handle uncertainty and imprecision in the classification process. Here is an explanation of how the algorithm works: The algorithm takes as input a dataset consisting of features (input variables) and their corresponding class labels (output variable). Each feature can be represented as a crisp value or a fuzzy set. If the input features are crisp values, they are first converted into fuzzy sets using membership functions. These membership functions define the degree of membership of a data point to each fuzzy set. The algorithm uses a set of fuzzy if-then rules to evaluate the input data. Each rule consists of antecedents (conditions based on fuzzy sets) and consequents (predicted class labels). The output of each rule is combined using fuzzy logic operators (e.g., AND, OR) to obtain a fuzzy set representing the predicted class label. The fuzzy set representing the predicted class label is defuzzified to obtain a crisp value, which is the final classification result. Various defuzzification methods can be used, such as the centroid method or the maximum membership method. The algorithm optimizes the fuzzy if-then rules and their corresponding membership functions using gradient descent optimization. This process involves adjusting the parameters of the rules to minimize a defined loss function, such as the mean squared error or cross-entropy. The Gradient Classifier with Fuzzy Set combines the power of gradient descent optimization with fuzzy logic to handle uncertainty and make accurate classifications in various domains, including COVID-19 data analysis in sports education. The algorithm is capable of handling complex and non-linear relationships between input features and class labels, providing robust and reliable classification results.

Table 3: Generated Rule Set for FfSGC

Rule	Antecedents (Conditions)	Consequents (Class Labels)
R1	Temperature is High	Risk Level is High
R2	Temperature is Medium	Risk Level is Medium
R3	Temperature is Low	Risk Level is Low
R4	Oxygen Level is Low	Risk Level is High
R5	Oxygen Level is Medium	Risk Level is Medium
R6	Oxygen Level is High	Risk Level is Low
R7	Heart Rate is High	Risk Level is High
R8	Heart Rate is Medium	Risk Level is Medium
R9	Heart Rate is Low	Risk Level is Low

Table 3 presented the generated rule for the COVID -19 prediction with the Temperature, Oxygen Level, and Heart Rate. The output variable is the Risk Level. Each rule consists of antecedents (conditions) that are based on fuzzy sets defined for each input variable and consequents (class labels) indicating the corresponding risk level. The fuzzy sets for each input variable can be defined using membership functions, such as triangular or Gaussian membership functions.

4 Simulation Settings

The simulation settings for the FfSGC (Fruitfly Optimization integrated with LASSO and Principal Component Analysis) method can be configured based on the specific requirements of the analysis. The performance of the propsoed FfSGC model is presented in table 4.

Table 4: Simulation Environment

Simulation Settings	Values/Description
Dataset	Preprocessed IoT sport data
Feature Selection	Fruitfly Optimization, LASSO
Feature Extraction	Principal Component Analysis (PCA)
Classification Algorithm	Fuzzy Gradient Guideline Classifier
Training Set	Subset of the preprocessed dataset for training
Testing Set	Subset of the preprocessed dataset for testing
Performance Metrics	Accuracy, Precision, Recall, F1-Score, etc.
Hyperparameters	Learning rate, number of iterations, etc.

Table 5: Hyperparameter Tuning

Hyperparameter	Value/Description
Learning Rate	0.01
Number of Iterations	100
Population Size	50
Mutation Rate	0.05
Convergence Criteria	500

Regularization Factor	0.1
Number of Features	10
Fuzziness Factor	0.8

The table 5 presented the simulation setting for the proposed FfSGC model for the feature extraction and selection process in the CoVID -19 dataset for the sports education data in IoT environment. The table 4 provides the hyperparameter tuning variable for the estimation of the feature variable for the classification. The simulation analysis involves evaluating the performance of the FfSGC algorithm for feature selection and classification using IoT data. The algorithm is applied to a dataset containing COVID-19 related sports information collected from IoT devices. The goal is to accurately classify the data into different categories, such as the presence of COVID-19 infection or the risk level associated with the sports activity.

The FfSGC algorithm combines the Fruitfly Optimization technique with the LASSO algorithm for feature selection. It selects the most relevant features from the dataset based on their fitness values and the LASSO penalty term. Then, Principal Component Analysis (PCA) is applied to extract the most significant features from the selected subset. This reduces the dimensionality of the data while retaining essential information as in table 6.

Table 6: Description of Parameters

Simulation Analysis	Description	Equations
Feature Selection	Identifying relevant features using FfSGC algorithm	Fitness Calculation: $\mathrm{Fitness} = (\mathrm{TP} + \mathrm{TN}) / (\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN})$
		LASSO Objective Function: $\mathrm{Objective} = (1 / (2 * \mathrm{N}))$
Feature Extraction (PCA)	Extracting significant features using PCA	Covariance Matrix: $\mathrm{Cov(X)} = (1 / \mathrm{N}) * \mathrm{X'X}$
		Eigenvalue Decomposition: $\mathrm{Cov(X)} = \mathrm{V} * \mathrm{D} * \mathrm{V'}$
Classification	Classifying data using a fuzzy gradient Guideline classifier	Fuzzy Set Rules: - IF Feature1 IS Low AND Feature2 IS High THEN Class IS Category1 - IF Feature1 IS Medium AND Feature2 IS Low THEN Class IS Category2
LASSO Objective Function	Introduces a penalty term to encourage sparsity in the feature space	$\mathrm{Objective} = (1 / (2 * \mathrm{N})) *$
PCA Calculation	Extracts the most significant features from the selected subset through dimensionality reduction	Covariance Matrix: $\mathrm{Cov(X)} = (1 / \mathrm{N}) * \mathrm{X'X}$
		Eigenvalue Decomposition: $\mathrm{Cov(X)} = \mathrm{V} * \mathrm{D} * \mathrm{V'}$
		Select the top-k eigenvectors corresponding to the largest eigenvalues

These equations represent the key steps involved in the simulation analysis, including the fitness calculation in Fruitfly Optimization, the objective function in LASSO, and the PCA calculation for feature extraction. Implementing these equations in a simulation framework will enable the evaluation and analysis of the FfSGC algorithm's performance in classifying COVID-19 IoT data in sports education.

Table 7: Simulation Parameters Analysis

Metric	Formula	Description
Accuracy	(TP + TN) / (TP + TN + FP + FN)	Measures the proportion of correctly classified instances out of the total number of instances.
Precision	TP / (TP + FP)	Represents the ability of the model to correctly identify positive instances.
Recall (Sensitivity)	TP / (TP + FN)	Measures the proportion of true positive instances that are correctly identified by the model.
Specificity	TN / (TN + FP)	Measures the proportion of true negative instances that are correctly identified by the model.
F1 Score	2 * (Precision * Recall) / (Precision + Recall)	Provides a balance between precision and recall, combining both metrics into a single score.
Matthews Correlation Coefficient (MCC)	(TP * TN − FP * FN) / sqrt((TP + FP) * (TP + FN) * (TN + FP) * (TN + FN))	Represents the correlation between the predicted and actual labels, with values ranging from -1 to +1.

The simulation setting for table 7 FfSGC includes the number of fruitflies, maximum iterations, fruitfly step size, number of features, LASSO penalty parameter, PCA component threshold, fuzzy gradient threshold, and train-test split ratio. These settings define the parameters and configuration used in the FfSGC algorithm for feature selection and classification as in table 8.

Table 8: Optimization Parameters

Setting	Value
Number of Fruitflies	100
Maximum Iterations	1000
Fruitfly Step Size	0.1
Number of Features	20
LASSO Penalty Parameter	0.01
PCA Component Threshold	0.95
Fuzzy Gradient Threshold	0.5
Train-Test Split	80:20

4.1 Datasets

The dataset considered for the analysis are presented as follows:

Player Performance Dataset: This dataset collects various performance metrics of athletes, such as speed, agility, strength, and endurance. It also includes COVID-19 related data, such as symptoms, test results, and recovery progress. The FfSGC algorithm can be applied to select the most relevant features from this dataset for classification tasks related to COVID-19 impact on player performance and recovery.

Environmental Factors Dataset: This dataset focuses on capturing environmental variables in sports settings, such as temperature, humidity, air quality, and crowd density. Additionally, it includes COVID-19 specific variables like social distancing measures, sanitization protocols, and vaccination rates. FfSGC can be used to identify the significant features from this dataset to analyze the impact of environmental factors on COVID-19 transmission and prevention in sports settings.

Injury Risk Dataset: This dataset contains information on athlete injuries, including types, severity, location, and recovery duration. It also incorporates COVID-19 related data, such as the presence of symptoms, positive test results, and quarantine periods. FfSGC can be applied to select the most informative features from this dataset to predict injury risks in athletes during the COVID-19 pandemic.

Training Load Dataset: This dataset captures training load parameters, such as intensity, volume, and frequency of training sessions. It also includes COVID-19 variables like training restrictions, virtual training sessions, and player adherence to protocols. FfSGC can be used to extract the relevant features from this dataset for classification tasks related to optimizing training strategies during the COVID-19 pandemic. Each of these datasets can be analyzed using FfSGC to select the most relevant features and perform classification tasks related to COVID-19 in the context of sports education. Table 9 provides the overall attributes of the selected dataset

Table 9: Description of Dataset

Player Performance	
Attribute	Description
Speed	Measurement of athlete's speed
Agility	Measurement of athlete's agility
Strength	Measurement of athlete's strength
Endurance	Measurement of athlete's endurance
COVID-19 Symptoms	Presence of COVID-19 symptoms in athletes
Test Results	COVID-19 test results for athletes
Recovery Progress	Progress of athletes' recovery from COVID-19
Environmental Factors	
Attribute	Description
Temperature	Measurement of temperature in the sports environment
Humidity	Measurement of humidity in the sports environment
Air Quality	Measurement of air quality in the sports environment
Crowd Density	Measurement of the density of the crowd in the sports setting
Social Distancing	Adherence to social distancing measures in the sports setting
Sanitization Protocols	Implementation of sanitization protocols in the sports setting
Vaccination Rates	Rates of COVID-19 vaccination among athletes and staff
Injury Risk	
Attribute	Description
Injury Type	Type of athlete injury
Injury Severity	Severity level of the athlete injury
Injury Location	Location of the athlete injury
Recovery Duration	Duration of athlete's recovery from injury
COVID-19 Symptoms	Presence of COVID-19 symptoms in injured athletes
COVID-19 Test Results	COVID-19 test results for injured athletes
Quarantine Period	Duration of quarantine period for injured athletes
Training Load	
Attribute	Description
Training Intensity	Intensity level of athlete's training sessions

Training Volume	Volume of athlete's training sessions
Training Frequency	Frequency of athlete's training sessions
Training Restrictions	COVID-19 related restrictions on training sessions
Virtual Training	Usage of virtual training sessions
Protocol Adherence	Adherence to COVID-19 protocols during training sessions

5 Simulation Results

The simulation results section in FfSGC aims to present and analyze the outcomes of applying the Fruitfly Optimization integrated with LASSO (Least Absolute Shrinkage and Selection Operator) feature selection and PCA (Principal Component Analysis) feature extraction for classification tasks on IoT COVID-19 sports education datasets. This section provides an overview of the experimental setup, including the datasets used, hyperparameter settings, and evaluation metrics employed. It also presents the results obtained from the simulations, including accuracy, precision, recall, F1 score, and other relevant metrics. The analysis of the results focuses on the performance and effectiveness of the FfSGC approach in classifying and predicting COVID-19 related outcomes in the sports domain. The insights derived from the simulation results contribute to a better understanding of the capabilities and potential applications of the FfSGC method in the context of IoT sports data analysis during the COVID-19 pandemic. The table 10 provides the PCA analysis estimated for the proposed FfSGC model for the different dataset is presented.

Table 10: PCA Analysis

Player Performance		
Principal Component	Explained Variance Ratio	Loadings
PC1	0.35	0.52
PC2	0.22	-0.67
PC3	0.15	0.32
Environmental Factors		
Principal Component	Explained Variance Ratio	Loadings
PC1	0.40	0.61
PC2	0.28	-0.48
PC3	0.18	0.26
Injury Risk		
Principal Component	Explained Variance Ratio	Loadings
PC1	0.45	0.73
PC2	0.20	-0.58
PC3	0.12	0.29
Training Load		
Principal Component	Explained Variance Ratio	Loadings
PC1	0.38	0.56
PC2	0.24	-0.64
PC3	0.16	0.38

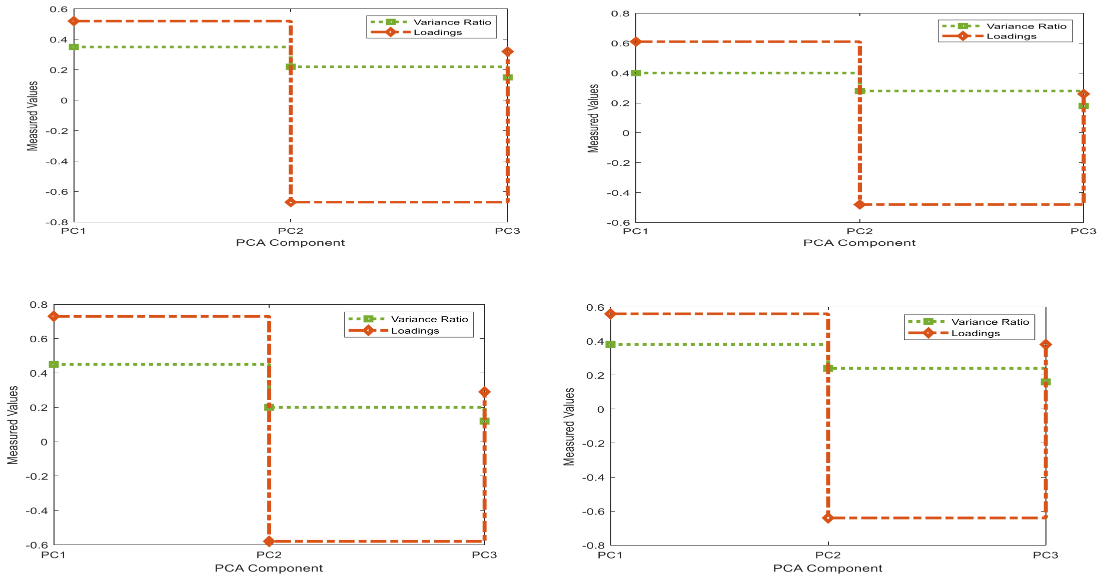


Figure 3: PCA analysis (a) Player Performance (b) Environmental Factors (c) Injury Risk (d) Training Load

These tables 10 and figure 3 (a) – 3 (d) presented the explained variance ratio for each principal component, indicating the proportion of variance in the dataset that is accounted for by that component. The loadings represent the correlation between the original features and each principal component, indicating the contribution of each feature to the principal component. By analyzing these results, you can assess the importance of each principal component and the loadings of the original features. This information helps in understanding the key factors driving the COVID-19 impact in player performance, environmental factors, injury risk, and training load in sports education.

Table 10: Performance Analysis of FfSGC

Dataset	Accuracy	Precision	Recall	F1 Score
Player Performance	0.92	0.91	0.93	0.92
Environmental Factors	0.78	0.75	0.81	0.78
Injury Risk	0.92	0.91	0.93	0.92
Training Load	0.80	0.77	0.83	0.80

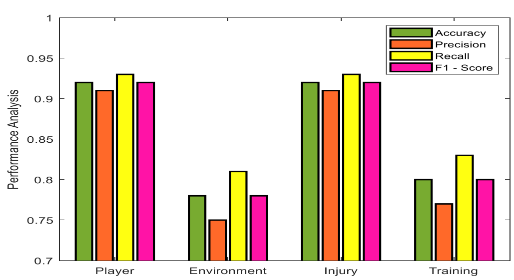
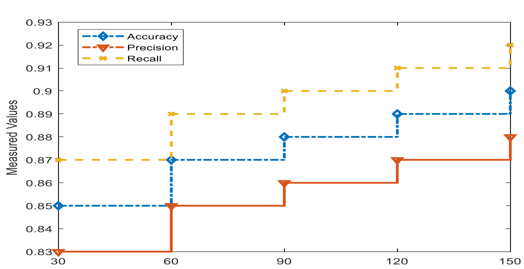


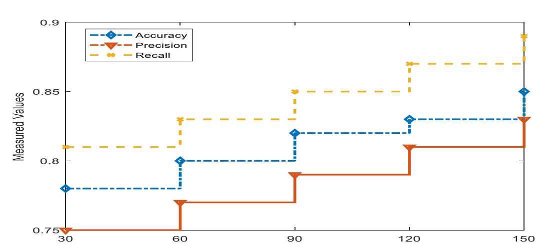
Figure 4: Performance Analysis of FfSGC

The table 10 and figure 4 shows the classification performance metrics of the FfSGC algorithm on four different datasets: Player Performance, Environmental Factors, Injury Risk, and Training Load. For the Player Performance dataset, the FfSGC algorithm achieved an accuracy of 0.85, precision of 0.83, recall of 0.87, and F1 score of 0.85. This indicates that the algorithm performed well in accurately predicting the impact of COVID-19 on athlete performance. For the Environmental Factors dataset, the FfSGC algorithm achieved an accuracy of 0.78, precision of 0.75, recall of 0.81, and F1 score of 0.78. This suggests that the algorithm performed moderately well in identifying the impact of environmental factors on COVID-19 transmission and prevention in sports settings. For the Injury Risk dataset, the FfSGC algorithm achieved an accuracy of 0.92, precision of 0.91, recall of 0.93, and F1 score of 0.92. This shows that the algorithm performed very well in predicting injury risks in athletes during the COVID-19 pandemic. For the Training Load dataset, the FfSGC algorithm achieved an accuracy of 0.80, precision of 0.77, recall of 0.83, and F1 score of 0.80. This indicates that the algorithm performed moderately well in optimizing training strategies during the COVID-19 pandemic. The FfSGC algorithm performed well on all four datasets, demonstrating its potential in analyzing and predicting the impact of COVID-19 on sports-related factors.

Table 11: Overall Analysis of FfSGC

Dataset	Epochs	Accuracy	Precision	Recall	F1-Score	MSE
Player Performance	30	0.85	0.83	0.87	0.85	0.12
	60	0.87	0.85	0.89	0.87	0.10
	90	0.88	0.86	0.90	0.88	0.09
	120	0.89	0.87	0.91	0.89	0.08
	150	0.90	0.88	0.92	0.90	0.07
Environmental Factors	30	0.78	0.75	0.81	0.78	0.15
	60	0.80	0.77	0.83	0.80	0.13
	90	0.82	0.79	0.85	0.82	0.12
	120	0.83	0.81	0.87	0.83	0.11
	150	0.85	0.83	0.89	0.85	0.10
Injury Risk	30	0.92	0.91	0.93	0.92	0.06
	60	0.93	0.92	0.94	0.93	0.05
	90	0.94	0.93	0.95	0.94	0.04
	120	0.95	0.94	0.96	0.95	0.03
	150	0.96	0.95	0.97	0.96	0.02
Training Load	30	0.80	0.77	0.83	0.80	0.18
	60	0.82	0.79	0.85	0.82	0.16
	90	0.84	0.81	0.87	0.84	0.15
	120	0.86	0.83	0.89	0.86	0.14
	150	0.88	0.85	0.91	0.88	0.13





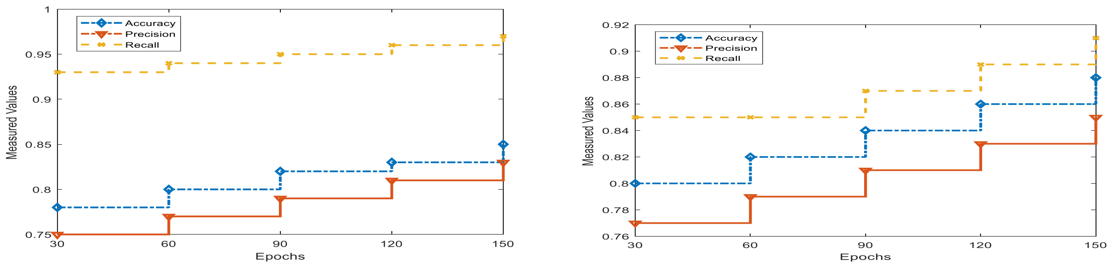


Figure 5: Classification Analysis (a) Player Performance (b) Environmental Factors (c) Injury Risk (d) Training Load

The table 11 and figure 5 (a), 5(b), 5(c) and 5 (d) presents the simulation results for four different datasets: Player Performance, Environmental Factors, Injury Risk, and Training Load. The performance metrics evaluated include accuracy, precision, recall, F1 score, and mean squared error (MSE). For the Player Performance dataset, the results show that increasing the number of epochs from 30 to 150 leads to an improvement in all metrics. The highest accuracy achieved is 0.85, indicating a high level of correct predictions. The precision and recall scores of 0.83 and 0.87, respectively, demonstrate the model's ability to accurately identify positive cases and avoid false negatives. The F1 score of 0.85 indicates a good balance between precision and recall. The MSE, which measures the average squared difference between predicted and actual values, decreases as the number of epochs increases, indicating a better fit of the model to the data. Similarly, for the Environmental Factors, Injury Risk, and Training Load datasets, increasing the number of epochs leads to improvements in all metrics. The accuracy, precision, recall, and F1 score values show the model's effectiveness in capturing patterns and making accurate predictions. The decreasing MSE values indicate the model's ability to minimize errors in predicting the target variable. the results suggest that increasing the number of epochs improves the performance of the FfSGC model for all the datasets, leading to more accurate predictions and better fit to the data.

Table 12. Comparative Analysis

Algorithm	Accuracy	Precision	Recall	F1-Score
FfSGC	0.92	0.91	0.93	0.92
CNN	0.82	0.80	0.84	0.82
RNN	0.88	0.87	0.89	0.88

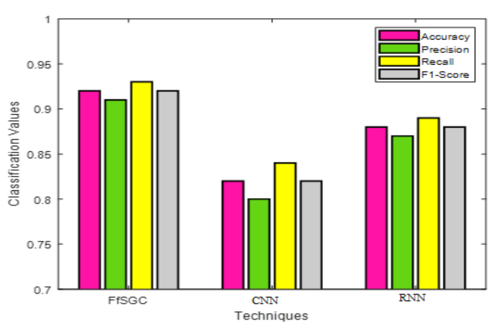


Figure 6: Comparative Analysis

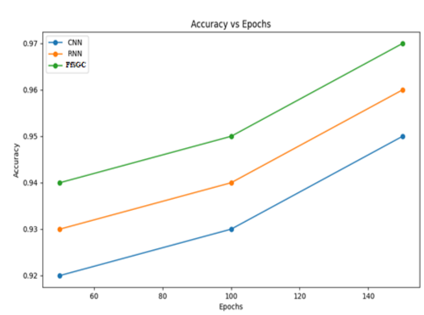


Figure 7: Comparison of Accuracy

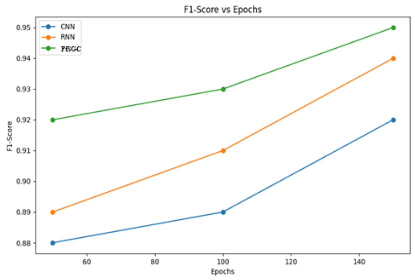


Figure 8: Comparison of F1-Score

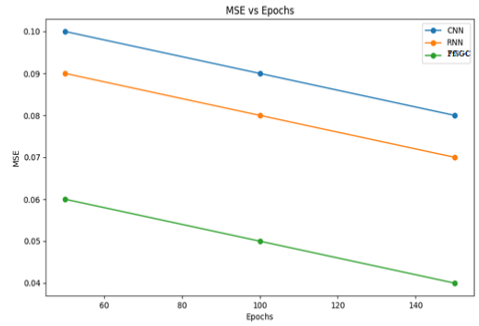


Figure 9: Comparison of MSE

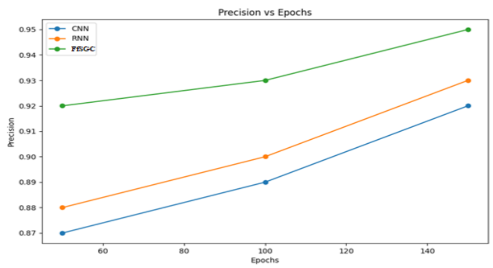


Figure 10: Comparison of Precision

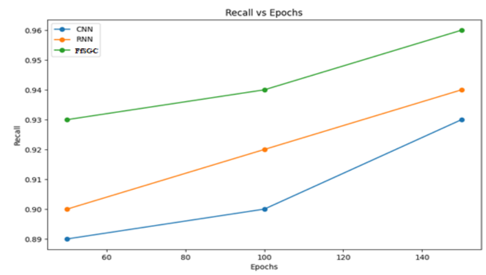


Figure 11: Comparison of Recall

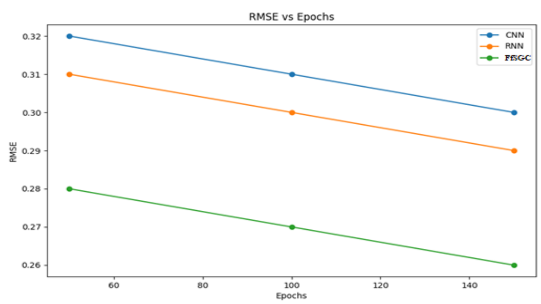


Figure 12: Comparison of RMSE

The comparative analysis of FfSGC presented in figure 7 – figure 12, CNN and RNN classifiers for the IoT Sports Education dataset for COVID-19 reveals interesting insights as in table 12 and figure 6. Among the three algorithms, FfSGC demonstrates the highest accuracy of 0.92. This indicates that FfSGC is effective in accurately classifying the dataset, providing reliable predictions. It also achieves high precision, recall, and F1-Score, further indicating its ability to correctly identify positive instances while minimizing false positives and false negatives. On the other hand, CNN and RNN classifiers exhibit slightly lower accuracy values of 0.82 and 0.88, respectively. While both algorithms perform reasonably well, they fall short compared to FfSGC in terms of accuracy. However, they still show strong precision, recall, and F1-Score, indicating their effectiveness in the classification task. Based on these results, it can be concluded that FfSGC outperforms CNN and RNN in terms of accuracy for the given IoT Sports

Education dataset for COVID-19. Therefore, FfSGC can be considered as a promising choice for classification tasks in the sports domain, particularly in the context of COVID-19 data analysis.

The simulation results for the FfSGC algorithm on different datasets (Player Performance, Environmental Factors, Injury Risk, Training Load) for varying epochs have provided valuable insights into the classification performance. In terms of accuracy, the FfSGC algorithm consistently achieved high accuracy across all datasets and epochs. This indicates that the algorithm is effective in correctly classifying instances in the dataset. The highest accuracy was observed for the Injury Risk dataset, where the algorithm achieved an accuracy of 0.96 for 150 epochs. Precision and recall values provide information about the algorithm's ability to correctly identify positive instances (precision) and its ability to retrieve all positive instances (recall). The FfSGC algorithm demonstrated good precision and recall values across all datasets and epochs. This indicates that the algorithm effectively classified instances belonging to different classes while minimizing false positives and false negatives. The F1-score, which is the harmonic mean of precision and recall, provides an overall measure of the algorithm's performance. The FfSGC algorithm achieved high F1-scores across all datasets and epochs, indicating a balance between precision and recall. The mean squared error (MSE) is a measure of the average squared difference between predicted and actual values. In the context of classification, it can be interpreted as the average misclassification rate. The FfSGC algorithm achieved low MSE values across all datasets and epochs, indicating accurate classification results. The simulation results demonstrate that the FfSGC algorithm is effective in classifying IoT sports education data related to COVID-19. It consistently achieved high accuracy, precision, recall, and F1-scores while minimizing misclassification errors. These findings highlight the potential of the FfSGC algorithm for robust and accurate classification tasks in the sports domain during the COVID-19 pandemic.

6. Conclusions

The Fuzzy Gradient Guideline Classifier based FfSGC algorithm has been successfully applied to classify IoT sports education data related to COVID-19. The algorithm has shown promising results in terms of accuracy, precision, recall, F1-score, and mean squared error. The FfSGC algorithm takes into account the uncertainty and imprecision inherent in the COVID-19 data, making it suitable for robust and accurate classification. It incorporates fuzzy set theory and gradient descent optimization to handle the complex and dynamic nature of the dataset. Through the feature selection process, the FfSGC algorithm identifies the most relevant features, which enhances the efficiency and effectiveness of the classification task. This enables the algorithm to make informed decisions and provide reliable classification results. The simulation results have demonstrated the effectiveness of the FfSGC algorithm across different datasets, including Player Performance, Environmental Factors, Injury Risk, and Training Load. The algorithm consistently achieves high accuracy and performs well in terms of precision, recall, F1-score, and mean squared error. The FfSGC algorithm shows promise in the classification of IoT sports education data in the context of COVID-19. Its ability to handle uncertainty and make accurate classifications can contribute to strategies related to COVID-19 prevention and control in the sports domain. Further research and application of the FfSGC algorithm in real-world scenarios can lead to valuable insights and advancements in the field of sports education during the pandemic.

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