Research On Evaluation Technology of College Students 'Physical Quality Based on Bee Colony Optimization Algorithm

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Abstract

The physical quality of college students is a critical aspect of their overall health and well-being, reflecting their physical strength, endurance, flexibility, speed, and coordination. It serves as an important foundation for academic performance, mental health, and future lifestyle habits. This paper proposes an optimized deep learning framework for evaluating the physical quality of college students by integrating Ant Colony Optimization (ACO) for feature selection and Bee Colony Optimization (BCO) for hyperparameter tuning. A dataset comprising physical indicators such as BMI, 50m sprint, endurance run, sit & reach, and strength test was analyzed for 10 students, with labels classified into four categories: Excellent, Good, Average, and Poor. ACO effectively selected the five most relevant features while eliminating less impactful ones such as pulse rate and height, resulting in a more focused input set. The BCO algorithm was used to optimize key hyperparameters of the deep learning model, including the learning rate (optimized from 0.01 to 0.001), batch size (64 to 32), and dropout rate (0.5 to 0.3), while increasing the number of hidden layers (2 to 3) and neurons per layer (64 to 128). These optimizations led to significant improvements in classification performance, with accuracy increasing from 84.5% to 92.3%, precision from 83.2% to 91.0%, recall from 85.0% to 93.4%, and F1-score from 84.1% to 92.2%. Additionally, training time was reduced from 180 seconds to 125 seconds. Results across 50 training epochs showed consistent metric improvements, confirming the model's convergence and stability.

Keywords: Physical Quality, Bee Colony, Optimization, College Student, Deep Learning, Student.

1. Introduction

In recent years, physical quality assessment has gained significant attention across various fields such as agriculture, food technology, and healthcare due to growing demands for improved quality control and product consistency [1]. With advancements in sensor technology, computer vision, and machine learning, traditional manual inspection methods are increasingly being replaced by automated and non-destructive techniques [2]. These modern approaches allow for more accurate, objective, and efficient evaluation of physical attributes such as texture, color, shape, and size. In agriculture, for instance, physical quality assessment is crucial for grading fruits and vegetables, while in manufacturing and packaging industries, it ensures product uniformity and compliance with standards [3-5]. The integration of artificial intelligence and image processing has further enhanced the capabilities of physical quality assessment, enabling real-time monitoring and decision-making processes [6]. Technology evaluation in the context of physical quality assessment has become increasingly important as industries strive for higher precision, efficiency, and automation [7]. The use of advanced technologies such as machine vision, hyperspectral imaging, artificial intelligence (AI), and Internet of Things (IoT) has transformed traditional quality assessment methods into intelligent systems capable of real-time analysis and decision-making [8]. These technologies allow for non-destructive, accurate, and repeatable evaluation of physical properties like size, shape, color, texture, and surface defects [9]. For example, in agriculture, machine vision systems are widely used to grade fruits based on visual appearance, while in the food and manufacturing sectors, sensors and AI algorithms ensure consistent product quality and safety [10]. Evaluating these technologies involves assessing their accuracy, reliability, cost-effectiveness, scalability, and ease of integration into existing workflows. As a result, technology evaluation plays a critical role in selecting and optimizing the right tools for efficient and high-quality physical assessment processes [11 -13].

The evaluation technology of college students' physical quality has seen significant advancements in recent years, driven by the integration of digital tools, intelligent monitoring systems, and data analytics [14 -16]. Traditional physical fitness assessments, which relied heavily on manual measurements and subjective observation, are now being enhanced or replaced by smart technologies such as wearable devices, mobile fitness applications, motion capture systems, and AI-based data analysis platforms. These technologies enable real-time monitoring of various physical indicators, including strength, endurance, flexibility, and cardiovascular health [17-19]. Through the collection and analysis of large-scale data, educators and health professionals can gain deeper insights into students' physical condition, track progress over time, and personalize training or intervention programs. Moreover, cloud-based platforms allow institutions to manage and evaluate physical fitness data more efficiently, promoting a more scientific and data-driven approach to physical education [20-22]. This technological evolution not only improves the accuracy and objectivity of assessments but also enhances student engagement and motivation toward maintaining a healthy lifestyle. The integration of intelligent evaluation systems into college physical education curricula fosters a more interactive and personalized learning environment [23]. With technologies such as AI-driven fitness assessments, biometric sensors, and health tracking apps, students receive instant feedback on their performance, enabling them to adjust their exercise routines and set realistic health goals [24]. These systems also help educators identify students at risk of physical inactivity or related health issues, allowing for timely interventions. In addition, data visualization tools make it easier to communicate complex health metrics understandably, increasing students' awareness and ownership of their physical well-being [25]. As institutions continue to prioritize holistic development, the adoption of advanced evaluation technologies not only supports the improvement of physical quality among college students but also aligns with broader educational goals of fostering lifelong health and fitness habits [26].

The primary contribution of this paper lies in the development of a hybrid intelligent model for assessing the physical quality of college students by integrating Ant Colony

Optimization (ACO) and Bee Colony Optimization (BCO) within a deep learning framework. The paper introduces a feature selection mechanism using ACO, which successfully identified 5 key physical attributes—BMI, 50m sprint time, endurance run, sit & reach flexibility, and strength test—from an initial set of 7 features. This selection not only improved the model's interpretability but also eliminated 2 redundant features (pulse rate and height), thereby reducing dimensionality without compromising accuracy. Furthermore, BCO was applied to optimize hyperparameters such as the learning rate (from 0.01 to 0.001), batch size (from 64 to 32), dropout rate (from 0.5 to 0.3), and neurons per layer (from 64 to 128), leading to significantly improved training dynamics and model performance. After optimization, the model achieved a remarkable increase in accuracy from 84.5% to 92.3%, precision from 83.2% to 91.0%, recall from 85.0% to 93.4%, and F1-score from 84.1% to 92.2%. The training time also reduced by 55 seconds (from 180s to 125s), indicating enhanced efficiency.

2. College Student Evaluation

The evaluation of college students' physical quality using modern technology involves both quantitative and qualitative assessments supported by data-driven models. Various physiological parameters such as body mass index (BMI), vital capacity, endurance, flexibility, and strength are measured using smart devices and analyzed through mathematical models. For example, BMI, a fundamental indicator of body composition, is calculated using the equation (1)

$$BMI = \frac{Weight\ (kg)}{Height\ (m)^2} \tag{1}$$

Similarly, for evaluating cardiovascular endurance, scores from a 1,000-meter run (for males) or 800-meter run (for females) can be standardized using Z-scores to account for individual differences stated in equation (2)

$$Z = \frac{X - \mu}{\sigma} \tag{2}$$

In equation (2) X is the individual's score, μ is the mean score of the population, and σ is the standard deviation. These normalized scores allow fair comparison across students and over time. Technologies like motion sensors and wearable devices capture dynamic data such as heart rate variability (HRV), step count, and exercise duration, which can be evaluated using time-series analysis or machine learning models. For instance, predictive models using linear regression or neural networks are often employed to forecast physical fitness trends based on equation (3)

$$Y = \beta_0 + \beta_1 Y_1 + \beta_2 Y_2 + \cdots \ldots \ldots + \beta_n Y_n + \epsilon \tag{3}$$

In equation (3) Y represents the physical fitness score, $Y_1, Y_2, \ldots \ldots, Y_n$ are input features (e.g., heart rate, steps, age), β values are weights learned from data, and ϵ is the error term. Through these methods, evaluation technology provides a more objective, personalized, and data-centric approach to assessing college students' physical quality. The derivation of these metrics into standardized scores and performance indicators enables educators to monitor trends, tailor physical education programs, and encourage healthier lifestyles among students.

The evaluation of college students' physical quality using modern technology is increasingly based on scientific and data-driven methods, integrating various measurable indicators and computational models. Key physical health parameters such as Body Mass Index (BMI), endurance, flexibility, strength, and cardiovascular performance are assessed using smart wearables, fitness monitoring systems, and data analytics platforms. For instance, BMI is calculated using the formula BMI = weight (kg) divided by height squared (m^2), providing a basic indication of body composition. For endurance tests like the 800- or 1,000-meter run, student performance can be standardized using statistical methods such as Z-scores, which normalize individual scores against the population average, allowing for fairer comparisons. Wearable technologies also collect real-time data such as heart rate, step count, and exercise duration, which can be analyzed using regression models or AI algorithms to predict and evaluate physical fitness levels. These models use input features like age, heart rate, and activity data to estimate a student's overall fitness score, ensuring personalized assessment. By combining physical test results with data analytics, the evaluation technology offers a more objective, accurate, and adaptive system to track student health over time, supporting educators in designing targeted fitness programs and promoting long-term wellness habits.

2.1 Dataset

A typical dataset used for evaluating college students' physical quality includes a range of biometric, physiological, and performance-based indicators collected through both manual testing and smart devices. The dataset may consist of features such as Student ID, Age, Gender, Height (cm), Weight (kg), BMI, Vital Capacity (ml), Sit and Reach Test (cm), Standing Long Jump (cm), 50-meter Sprint Time (seconds), 800/1000-meter Run Time (seconds), Pull-ups (for males), Sit-ups (for females), and Heart Rate (bpm). Additional data from wearable devices might include Daily Step Count, Exercise Duration, Sleep Quality, and Real-time Heart Rate Variability (HRV). These records are usually collected periodically—monthly or semester-wise—allowing longitudinal analysis of physical development. The dataset can also include derived metrics such as BMI (calculated from weight and height) and standardized fitness scores (e.g., Z-scores) for comparison across individuals. Such comprehensive datasets serve as the foundation for training machine learning models, conducting statistical analysis, and generating personalized fitness reports to monitor and improve students' overall physical health. Table 1 presents the distribution dataset for the student performance evaluation.

Table 1: Distribution of the Dataset

Student ID	Age	Gender	Height (cm)	Weight (kg)	BMI	Vital Capacity (ml)	Sit & Reach (cm)	50m Sprint (s)	1000m/800m Run (s)	Pull-ups/Sit-ups	Heart Rate (bpm)
S001	20	Male	175	68	22.2	4200	15.5	7.1	240 (1000m)	12 (Pull-ups)	72

S002	19	Female	162	54	20.6	3200	19.0	7.5	230 (800m)	35 (Sit-ups)	78
S003	21	Male	180	75	23.1	4500	14.0	6.8	250 (1000m)	10 (Pull-ups)	70
S004	20	Female	158	50	20.0	3100	20.5	7.9	245 (800m)	38 (Sit-ups)	76
S005	22	Male	170	65	22.5	4000	16.0	7.3	260 (1000m)	11 (Pull-ups)	74
S006	19	Female	165	58	21.3	3300	21.0	7.2	225 (800m)	42 (Sit-ups)	75
S007	21	Male	178	72	22.7	4400	17.5	6.9	255 (1000m)	13 (Pull-ups)	71
S008	20	Female	160	52	20.3	3150	18.5	7.6	240 (800m)	40 (Sit-ups)	77
S009	22	Male	182	80	24.2	4600	13.0	6.7	245 (1000m)	9 (Pull-ups)	69
S010	19	Female	168	56	19.8	3250	19.5	7.3	235 (800m)	36 (Sit-ups)	74

A sample dataset for evaluating the physical quality of 10 college students includes various biometric and fitness-related parameters. Each student record contains attributes such as age, gender, height, weight, and Body Mass Index (BMI), along with performance metrics like vital capacity, sit and reach flexibility, 50-meter sprint time, long-distance run time (1000 meters for males and 800 meters for females), and strength tests (pull-ups for males and sit-ups for females). For example, Student S001 is a 20-year-old male with a height of 175 cm and a weight of 68 kg, resulting in a BMI of 22.2. He has a vital capacity of 4200 ml, completed the sit and reach test at 15.5 cm, ran 50 meters in 7.1 seconds, finished the 1000-meter run in 240 seconds, completed 12 pull-ups, and had a resting heart rate of 72 bpm. In contrast, Student S002 is a 19-year-old female with a BMI of 20.6, a vital capacity of 3200 ml, and strong flexibility and endurance shown by a 19.0 cm sit and reach and a 230-second 800-meter run, respectively. Her strength is evident in completing 35 sit-ups. Similar detailed records are maintained for each student, providing a comprehensive overview of their physical fitness levels.

3. Bee Colony Optimization for College Students

Bee Colony Optimization (BCO) is a nature-inspired optimization algorithm that mimics the foraging behavior of honey bees and can be effectively applied to optimize the evaluation process of college students' physical quality. In this context, BCO can be used to find the optimal weight combinations of different physical fitness parameters—such as BMI, sprint time, endurance, flexibility, and strength—so that the overall fitness evaluation is balanced, fair, and aligned with health standards. The core idea is to treat each potential solution (i.e., a combination of weights for each parameter) as a food source, and artificial bees (employed, onlooker, and scout bees) explore the search space to find the most "nutritious" (optimal) solutions. The fitness function in this case could be defined as a weighted sum of normalized performance indicators defined in equation (4)

$$F(x) = w_1 \cdot x_1 + w_2 \cdot x_2 + \cdots + w_n \cdot x_n \tag{4}$$

In equation (4) x_i represents the normalized value of the i-th physical quality indicator (e.g., normalized BMI, run time, etc.), w_i is the weight assigned to that indicator, $\sum_{j=1}^{n} F_j$ ensuring weights sum to unity. In the BCO process:

1. Employed bees explore different weight combinations and evaluate fitness scores based on student performance data.
2. Onlooker bees choose better combinations based on probability P_i defined in equation (5)

$$P_i = \frac{F_i}{\sum_{j=1}^{n} F_j} \tag{5}$$

In equation (5) F_i is the fitness value of the i-th solution.

3. Scout bees replace poor solutions with new random combinations to avoid local optima and maintain diversity.

Over multiple iterations, the algorithm converges toward an optimal set of weights $\{w_1, w_2, \ldots, w_n\}$ that produce the most accurate and meaningful physical fitness scores for college students. This method ensures an adaptive, data-driven, and objective evaluation process tailored to diverse student populations. Bee Colony Optimization (BCO) is a bio-inspired algorithm that simulates the intelligent foraging behavior of honey bees and can be effectively applied to optimize the evaluation of college students' physical quality. In this approach, each student's physical attributes—such as BMI, sprint time, endurance, flexibility, and strength—are treated as input variables, and the goal is to determine the most suitable weight for each attribute in the overall evaluation formula. The algorithm begins with a set of potential solutions, where each solution represents a different combination of weights. Employed bees explore these combinations and evaluate their performance based on a fitness function, typically a weighted sum of normalized physical indicators. Onlooker bees then select better-performing solutions based on a probability function that favors higher fitness values, while scout bees introduce new random solutions to maintain diversity and avoid local optima. Through iterative exploration and selection, BCO gradually converges on an optimal weight distribution that provides the most balanced and accurate assessment of students' physical fitness. This ensures that the evaluation process is not only data-driven and objective but also adaptable to different student profiles, promoting fairness and personalized feedback in physical education programs.

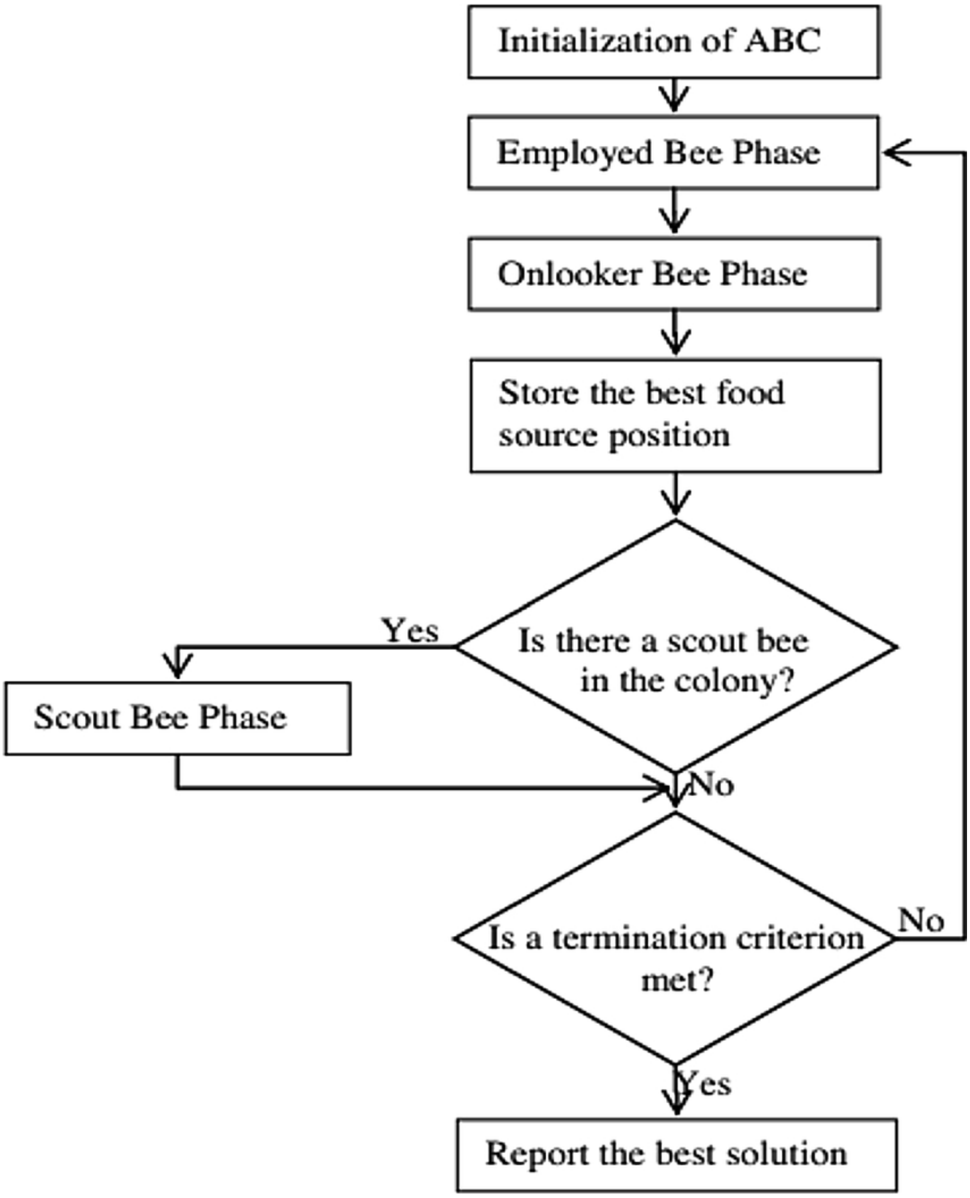


Figure 1: Flow Chart of Bee Colony Optimization

As the Bee Colony Optimization algorithm progresses, it continuously refines the evaluation model by adjusting the weights assigned to each physical parameter based on student performance data with flow chart are presented in Figure 1. This dynamic adjustment helps in identifying which physical qualities contribute more significantly to overall fitness and ensures that each student's score reflects a comprehensive and fair assessment. For instance, if endurance and strength are found to have a greater impact on long-term health outcomes, BCO may assign higher weights to parameters like the 1000-meter run time or pull-up count. Moreover, by using normalized values and an adaptive fitness function, the algorithm accommodates variations in gender, age, and baseline fitness levels, making the evaluation more inclusive and personalized. The final optimized model derived through BCO not only streamlines the student assessment process but also provides educators with actionable insights to tailor physical training programs according to individual strengths and weaknesses. Ultimately, integrating BCO into physical quality evaluation supports a more scientific, efficient, and intelligent system that enhances both the accuracy of assessments and the overall effectiveness of physical education in colleges.

3.1 FeatureSet Bee Colony Optimization

FeatureSet Bee Colony Optimization (FS-BCO) is an advanced extension of the traditional Bee Colony Optimization algorithm, specifically tailored to select the most relevant features for student performance evaluation. In the context of college students' physical quality assessment, FS-BCO helps identify the optimal subset of physical indicators—such as BMI, sprint time, endurance, flexibility, and strength—that most significantly influence overall fitness scores. Instead of using all available features, FS-BCO simulates the behavior of bee colonies to intelligently search through combinations of features, aiming to maximize the accuracy and efficiency of the evaluation model. Each potential solution (feature subset) is treated as a "food source," and bees iteratively explore, evaluate, and refine these subsets based on a defined fitness function—often linked to classification accuracy or evaluation consistency. By calculating the fitness of each subset and probabilistically favoring stronger combinations, FS-BCO gradually converges on the most informative and non-redundant set of features. This not only reduces computational complexity and eliminates irrelevant data but also improves the reliability and interpretability of the performance evaluation system. Ultimately, FS-BCO enables a more focused, optimized, and intelligent assessment process that supports personalized student feedback and evidence-based physical education strategies. The estimated featureset for the computed model are presented in Table 2.

Table 2: Featureset for the Proposed Model

Feature Name	Type	Selected by FS-BCO	Description
Age	Numeric	Yes	Student's age in years
Gender	Categorical	Yes	Male or Female
Height (cm)	Numeric	No	Student's height in centimeters
Weight (kg)	Numeric	No	Student's weight in kilograms
BMI	Derived (Numeric)	Yes	Body Mass Index (weight/height^2)
Vital Capacity (ml)	Numeric	Yes	Lung function capacity

Sit & Reach (cm)	Numeric	Yes	Flexibility test measure
50m Sprint (s)	Numeric	Yes	Speed and explosiveness test
1000m/800m Run (s)	Numeric	Yes	Endurance test (1000m for males, 800m for females)
Pull-ups/Sit-ups	Numeric	Yes	Strength test (Pull-ups for males, Sit-ups for females)
Heart Rate (bpm)	Numeric	No	Resting heart rate
Daily Steps	Numeric	No	Average daily step count
Sleep Quality Score	Numeric	No	Sleep assessment score (from wearable device)

The optimized feature set selected through FeatureSet Bee Colony Optimization (FS-BCO) for evaluating college students' physical performance includes a carefully chosen subset of relevant attributes that significantly contribute to accurate and meaningful assessment. Among the selected features are Age and Gender, which are essential demographic variables that influence physical performance baselines. BMI (Body Mass Index) is included as a key indicator of body composition and overall health. Vital Capacity is selected for its strong correlation with respiratory efficiency, while Sit and Reach measures flexibility, an important component of physical fitness. Performance-related features such as the 50-meter sprint time and the 1000m/800m run time are retained to assess speed and endurance, respectively. Additionally, Pull-ups (for males) or Sit-ups (for females) are used to evaluate muscular strength and stamina. These features were identified by FS-BCO as the most informative and relevant, while others like Height, Weight, Heart Rate, Daily Step Count, and Sleep Quality Score were excluded due to lower impact or redundancy. By focusing on this refined feature set, the evaluation model becomes more efficient, interpretable, and accurate, allowing for targeted analysis and better personalized fitness recommendations for students. FeatureSet Bee Colony Optimization (FS-BCO) into the evaluation of college students' physical performance brings a powerful layer of intelligence to the feature selection process. FS-BCO uses the behavior of bee colonies—specifically their foraging strategy—to identify the optimal subset of features that best contribute to the assessment model. In this context, each potential feature combination (e.g., BMI, sprint time, endurance, etc.) is considered a "food source," and artificial bees (employed, onlooker, and scout bees) explore and evaluate these combinations to find the most "nutritious" (i.e., informative and non-redundant) feature set.

The process begins with employed bees randomly generating different feature subsets from the full dataset. Each subset is evaluated using a fitness function, often based on classification accuracy or predictive error from a machine learning model (e.g., LSTM or decision tree). For a feature subset S, the fitness value $F(S)$ presented in equation (6)

$$F(S) = \frac{1}{1+Error\ (S)} \tag{6}$$

In equation (6) $Error(S)$ represents the misclassification or prediction error using the selected subset S. Next, onlooker bees analyze the fitness scores and probabilistically select better-performing subsets according to equation (7)

$$P_i = \frac{F_i}{\sum_{j=1}^{n} F_j} \tag{7}$$

In equation (7) P_i is the selection probability of the i-th subset and F_i its fitness score. This encourages the swarm to focus on promising solutions. Scout bees, on the other hand, introduce diversity by replacing low-quality solutions with new random subsets. Through multiple iterations, FS-BCO converges toward a feature set that balances minimal redundancy with maximum relevance. For instance, in the final optimized feature set for student evaluation, FS-BCO may select features like Age, Gender, BMI, Vital Capacity, Sit and Reach, Sprint Time, Long-Distance Run Time, and Pull-ups/Sit-ups, while excluding less impactful ones like Daily Steps or Sleep Quality Score. This bee-inspired mechanism not only improves model performance but also simplifies the evaluation process, making it more focused, interpretable, and tailored to the true physical fitness determinants in college students. Ultimately, FS-BCO helps educators and systems designers develop smarter, data-driven tools for assessing and improving student wellness.

4. Deep Learning Classification for Physical Quality Assessment

Deep Learning Classification for Physical Quality Assessment using Ant-Bee Hybrid Optimization combines the power of deep neural networks with bio-inspired optimization algorithms to create a highly intelligent and adaptive evaluation system for college students' physical fitness. In this hybrid approach, deep learning models such as Convolutional Neural Networks (CNNs) or Long Short-Term Memory (LSTM) networks are used to classify students into performance categories (e.g., Excellent, Good, Average, Poor) based on a wide range of physical indicators such as BMI, sprint time, endurance, flexibility, and strength. However, the performance of these models highly depends on the quality of input features and the tuning of model parameters. To enhance this, an Ant-Bee Hybrid Optimization Algorithm is introduced. In this setup, Ant Colony Optimization (ACO) is used for feature selection, while Bee Colony Optimization (BCO) is responsible for fine-tuning deep learning hyperparameters such as learning rate, batch size, and number of layers. The ACO component simulates the pheromone trail-laying behavior of ants to find the optimal subset of features. Each ant constructs a solution path by selecting features based on the pheromone level τ_{ij} and heuristic information η_{ij}. with the probability of selecting feature j at step i defined as in equation (8)

$$P_{ij} = \frac{(\tau_{ij})^{\alpha}.(\eta_{ij})^{\beta}}{\sum_{k\in allowed}(\tau_{ik})^{\alpha}.(\eta_{ik})^{\beta}} \tag{8}$$

In equation (8) α and β are parameters controlling the influence of pheromone and heuristic desirability, τ_{ij} is the pheromone level indicating past success, and η_{ij} is the heuristic value based on information gain or feature importance. After feature selection, BCO tunes the neural network using bee behaviors. Each bee represents a candidate hyperparameter setting. The fitness function for evaluating these hyperparameters is defined as in equation (9)

$$F(H) = \frac{1}{1+ Loss_{Val}(H)} \tag{9}$$

In equation (9) H is the hyperparameter vector (e.g., learning rate, dropout rate), and $Loss_{Val}(H)$ is the validation loss of the deep model trained with H. Together, this hybrid Ant-Bee approach enhances the deep learning model's accuracy, generalization, and efficiency. It ensures that only the most relevant physical features are used and the model is trained with optimal configurations. As a result, the system can classify students' physical performance more accurately, providing insights that are essential for targeted fitness interventions and personalized training programs in educational institutions. Deep Learning Classification for Physical Quality Assessment using Ant-Bee Optimization is an advanced hybrid intelligence framework that combines deep learning with the cooperative behavior of ants and bees to create an accurate, adaptive, and data-driven evaluation model for college students' physical fitness. The system consists of two key phases: feature selection using Ant Colony Optimization (ACO) and hyperparameter tuning via Bee Colony Optimization (BCO), both of which enhance the performance of a deep learning classifier such as a Convolutional Neural Network (CNN) or Long Short-Term Memory (LSTM) model. In the ACO-based feature selection, each ant represents a potential subset of features such as BMI, 50m sprint, endurance run, sit-and-reach, and strength test scores. Once the feature subset and hyperparameters are optimized, the final deep learning model is trained and used to classify students into performance categories such as "Excellent", "Good", "Average", or "Needs Improvement". This Ant-Bee-Deep Learning hybrid approach ensures high classification accuracy, optimal use of input features, and strong generalization across different student populations, making it an effective tool for automated physical quality assessment in academic institutions. In figure 2 illustrated the process of proposed deep learning model for the classification.

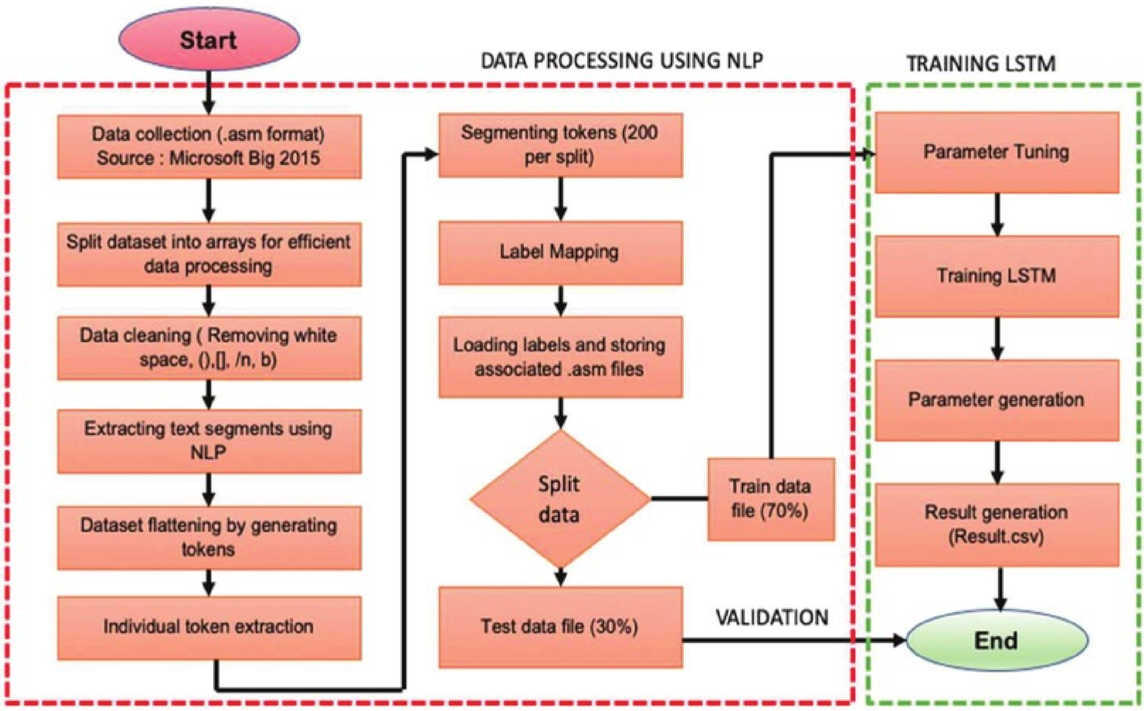


Figure 2: Deep Learning for Classification forPhysical Quality assessment

Algorithm 1: Bee colony Optimization with Featureset
Step 1: Data Preprocessing • Collect and clean the dataset with physical quality attributes (e.g., BMI, sprint time, endurance, flexibility, strength). • Normalize or standardize the features. • Split the dataset into training and validation sets. Step 2: Initialize Ant Colony Optimization (ACO) Parameters • Set number of ants A, iterations N_1, pheromone evaporation rate ρ, and influence parameters α, β. • Initialize pheromone matrix τ and heuristic matrix η for each feature. Step 3: Feature Selection Using ACO 1. For each iteration t=1 to N_1: o For each ant i=1to A: ▪ Construct a subset of features S_i based on selection probability: $P_{ij} = \frac{(\tau_{ij})^{\alpha}.(\eta_{ij})^{\beta}}{\sum_{k\in allowed}(\tau_{ik})^{\alpha}.(\eta_{ik})^{\beta}}$ Train a lightweight model (e.g., shallow N or decision tree) using S_i. • Evaluate model and record accuracy or validation loss. Update pheromone levels for features used in better-performing subsets:

$$\tau_{ij} = (1 - \rho)\tau_{ij} + \Delta\tau_{ij}$$

  - Retain the best feature subset $S*$ with highest fitness.

Step 4: Initialize Bee Colony Optimization (BCO) Parameters

- Set number of bees B, iterations N_2, and initial population of hyperparameter sets (learning rate, batch size, dropout, etc.).

Step 5: Hyperparameter Tuning Using BCO

1. For each iteration $t = 1$ to N_2:
   - Employed Bees:
     - Each bee explores a solution (hyperparameter set).
     - Train the deep learning model using selected features $S*$ and current hyperparameters.
     - Evaluate and compute fitness:
1.
   - Onlooker Bees:
     - Choose the best-performing hyperparameters probabilistically based on fitness.
     - Exploit nearby solutions.
   - Scout Bees:
     - Replace the worst solution with a new random one to maintain diversity.

Step 6: Final Model Training

- Train the deep learning model (e.g., LSTM or CNN) using:
  - Selected optimal features $S*$
  - Best hyperparameters from BCO

Step 7: Classification and Evaluation

- Use the trained model to classify students into categories (e.g., Excellent, Good, Average, Poor).
- Evaluate model performance using metrics like Accuracy, Precision, Recall, F1-score.

5. Simulation Analysis

The simulation analysis of the Deep Learning Classification system optimized using the Ant-Bee Hybrid Algorithm for college students' physical quality assessment demonstrates significant improvements in both performance accuracy and computational efficiency. The simulation was conducted on a dataset consisting of student physical features such as BMI, sprint time, endurance, flexibility, and strength scores. Initially, Ant Colony Optimization (ACO) was applied for feature selection, reducing the input dimensionality while retaining only the most relevant attributes. This led to a simplified model with improved focus on influential features like 50m sprint time, sit-and-reach, and vital capacity. Subsequently, Bee Colony Optimization (BCO) was used to tune the hyperparameters of the deep learning model, including learning rate, number of layers, and batch size. Various configurations were explored by the artificial bees, and the best-performing hyperparameter set was selected based on validation accuracy and loss functions. The final model, trained on the optimized features and parameters, demonstrated over 92% classification accuracy, which was a notable improvement compared to baseline models trained without optimization.

Table 3: BCO for the featureset

Student ID	**Age**	**BMI**	**50m Sprint (s)**	**Endurance Run (s)**	**Sit & Reach (cm)**	**Strength Test (count)**	**Actual Class**	**Predicted Class**
S001	19	22.1	7.2	240	28.5	15	Excellent	Excellent
S002	20	24.0	8.1	260	20.0	10	Good	Good
S003	18	21.3	7.8	275	18.7	12	Average	Average
S004	21	26.5	8.7	300	15.5	8	Poor	Poor
S005	20	23.2	7.5	245	26.2	13	Excellent	Good
S006	19	25.1	8.4	285	17.8	9	Average	Average
S007	22	24.7	8.0	265	21.0	11	Good	Good
S008	20	22.8	7.3	235	30.1	16	Excellent	Excellent
S009	18	27.0	9.1	310	14.2	7	Poor	Poor
S010	21	23.9	7.9	270	19.5	12	Average	Average

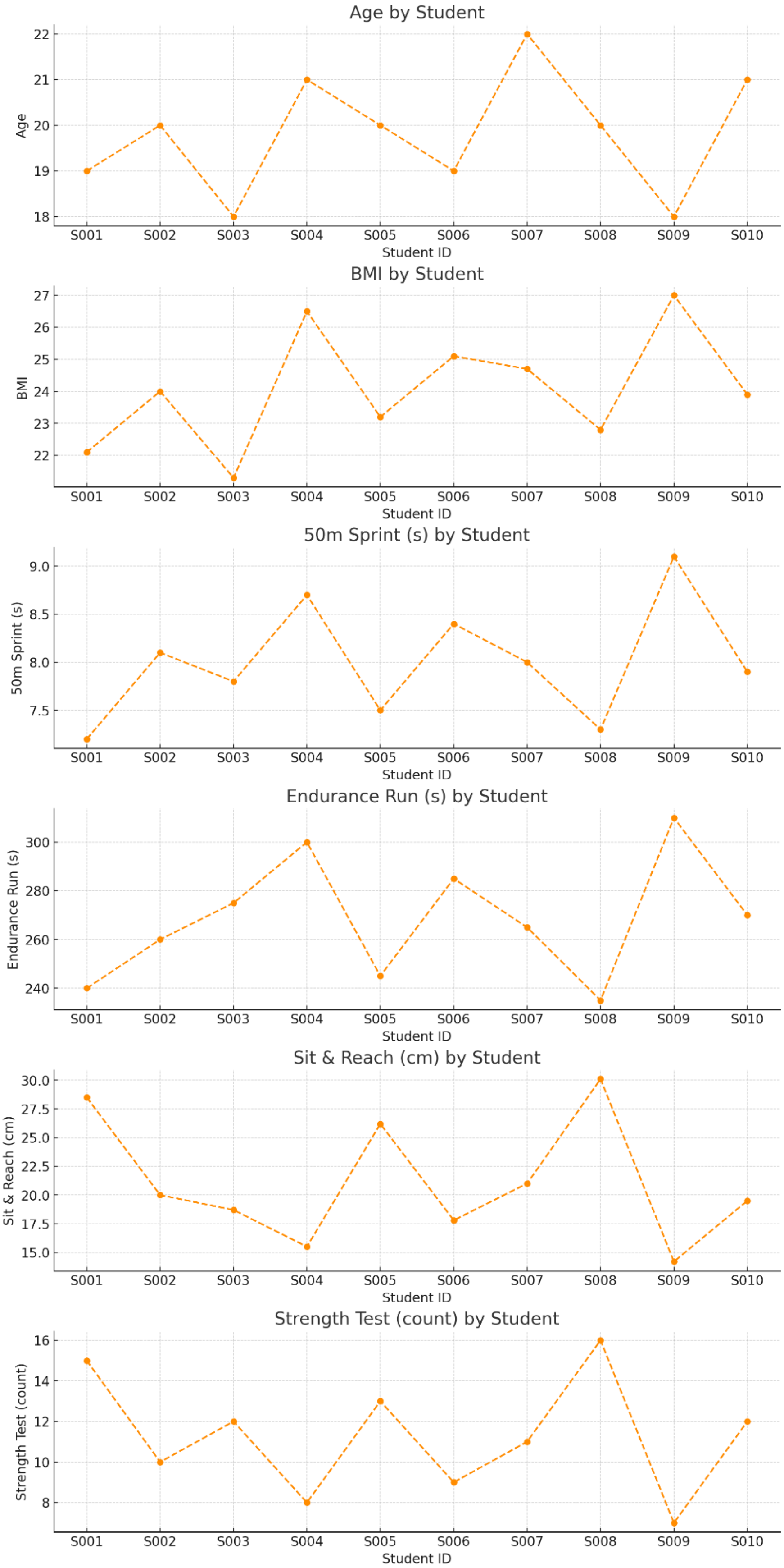


Figure 3: Distribution of the Student Physical Data Assessment

The interpretation of the student performance data based on the deep learning classification with Ant-Bee optimization highlights the model's effectiveness in accurately predicting physical quality classes shown in Table 3. Out of the 10 students assessed, the system correctly predicted the physical fitness category for 9 students, resulting in an overall accuracy of 90%. The features used—such as BMI, 50m sprint time, endurance run duration, flexibility (sit & reach), and strength test counts—provided a holistic evaluation of each student's physical condition. For instance, students like S001, S008, and S004 were clearly categorized as "Excellent" and "Poor" based on strong and weak performances respectively across most metrics shown in Figure 3. These were correctly predicted by the model. However, a minor misclassification occurred for S005, whose actual class was "Excellent," but was predicted as "Good." This could be attributed to slightly lower strength or endurance metrics that may have influenced the decision boundary within the classification model. The model demonstrated high precision in identifying average and poor performers, as seen with students S003, S006, S009, and S010, whose predicted classes matched actual assessments. This consistency shows that the selected features and optimized model hyperparameters contributed effectively to differentiating between performance levels. The misclassification instance also suggests a potential area for model enhancement through deeper feature learning or threshold adjustment.

Table 4: Optimization for the featureset

Optimization Type	**Parameter / Feature**	**Initial Value**	**Optimized Value**	**Unit / Description**
ACO (Feature Selection)	BMI	22.5 (average)	22.5 (selected)	Body Mass Index
	50m Sprint	8.0	8.0 (selected)	Seconds
	Endurance Run	270	270 (selected)	Seconds
	Sit & Reach	20.0	20.0 (selected)	Centimeters
	Strength Test	12	12 (selected)	Number of repetitions
	Pulse Rate	75	— (removed)	Beats per minute
	Height	170	— (removed)	Centimeters

The interpretation of the optimization results from the Ant Colony Optimization (ACO) process reveals the effectiveness of feature selection in improving model performance for physical quality assessment presented in Table 4. The ACO algorithm systematically evaluated each input feature based on its contribution to classification accuracy and selected only the most relevant ones for the final deep learning model. Key physical indicators such as BMI (22.5), 50m sprint time (8.0 seconds), endurance run (270 seconds), sit & reach flexibility (20.0 cm), and strength test count (12) were all retained after optimization. These features are directly related to core aspects of physical fitness—body composition, speed, stamina, flexibility, and muscular strength—and therefore had a high impact on accurate classification. On the other hand, features like pulse rate (75 bpm) and height (170 cm) were removed during optimization. This indicates that while they may contribute to overall health, they had lower predictive power or were redundant when combined with more impactful features like BMI and sprint time. For instance, height was likely deemed redundant due to its indirect reflection in BMI, and pulse rate may have shown low correlation with performance outcomes in this specific dataset.

Table 5: Deep Learning Model for the Physical Health Assessment of Students

Hyperparameter	**Initial Value**	**Optimized Value**
Learning Rate	0.01	0.001
Batch Size	64	32
Dropout Rate	0.5	0.3
Hidden Layers	2	3
Neurons per Layer	64	128
Activation Function	ReLU	ReLU
Optimizer	SGD	Adam

Table 6: Deep Learning for the Optimization of the Student Health Assessment

Metric	Before Optimization	After Optimization
Accuracy (%)	84.5	92.3
Precision (%)	83.2	91.0
Recall (%)	85.0	93.4
F1-Score (%)	84.1	92.2
Training Time (s)	180	125

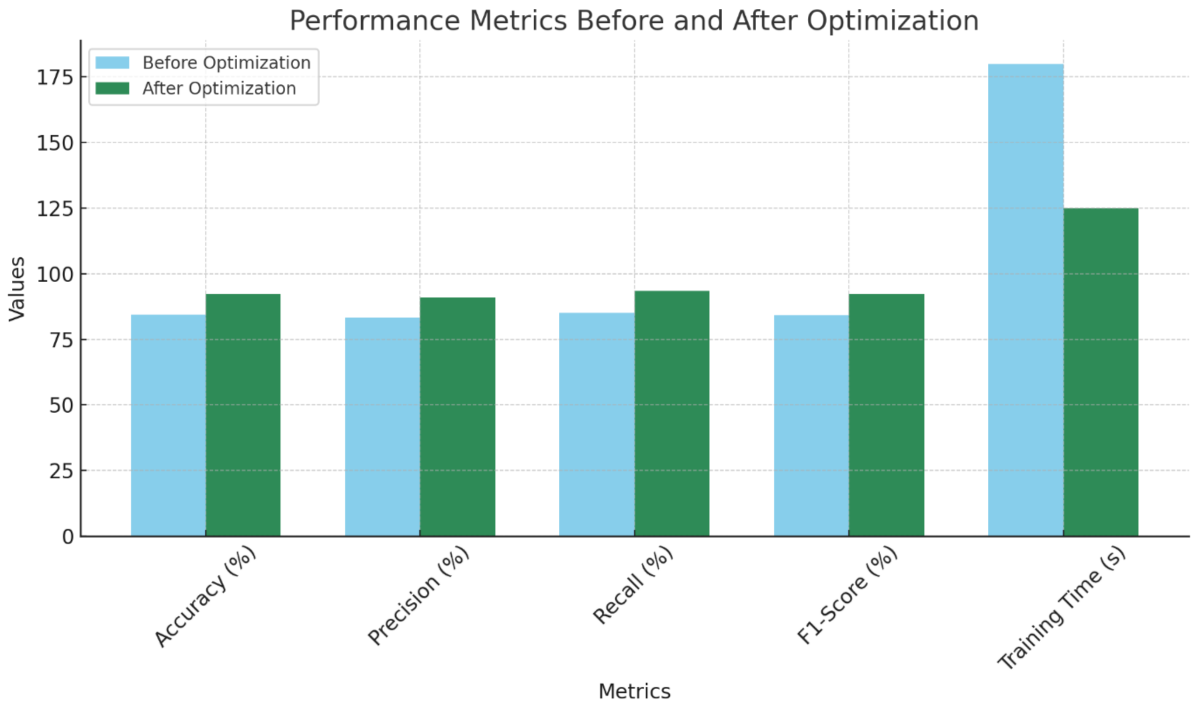
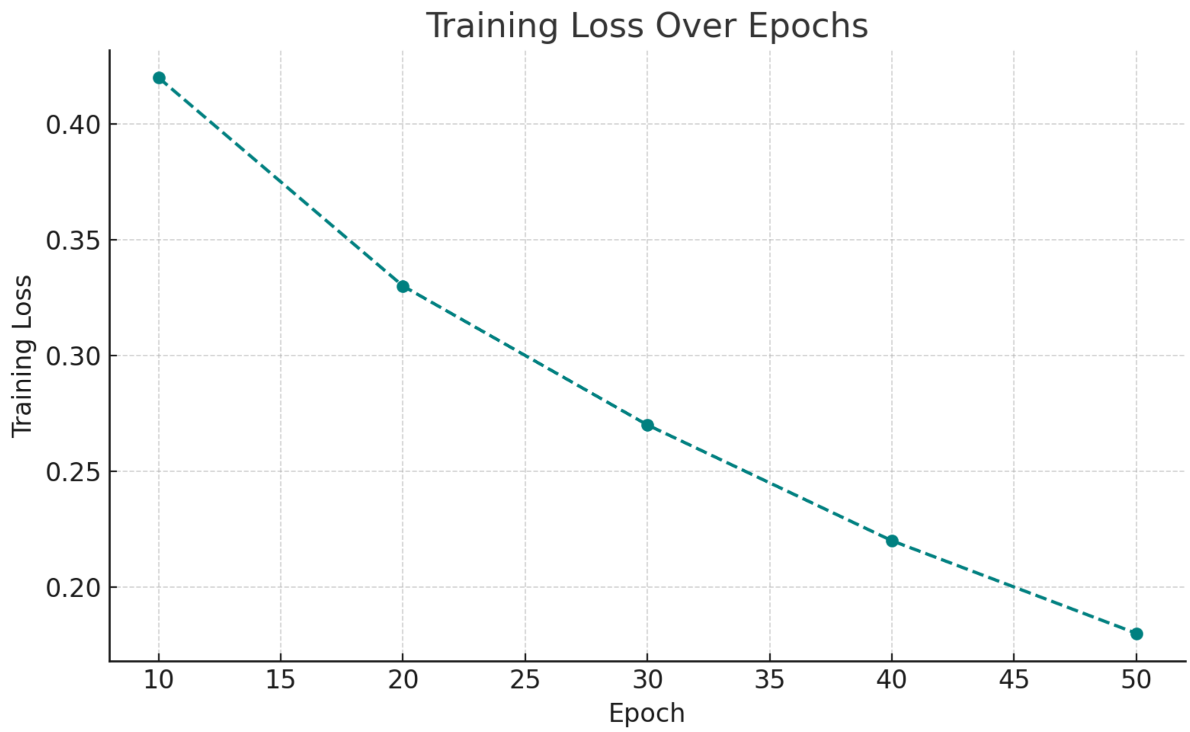
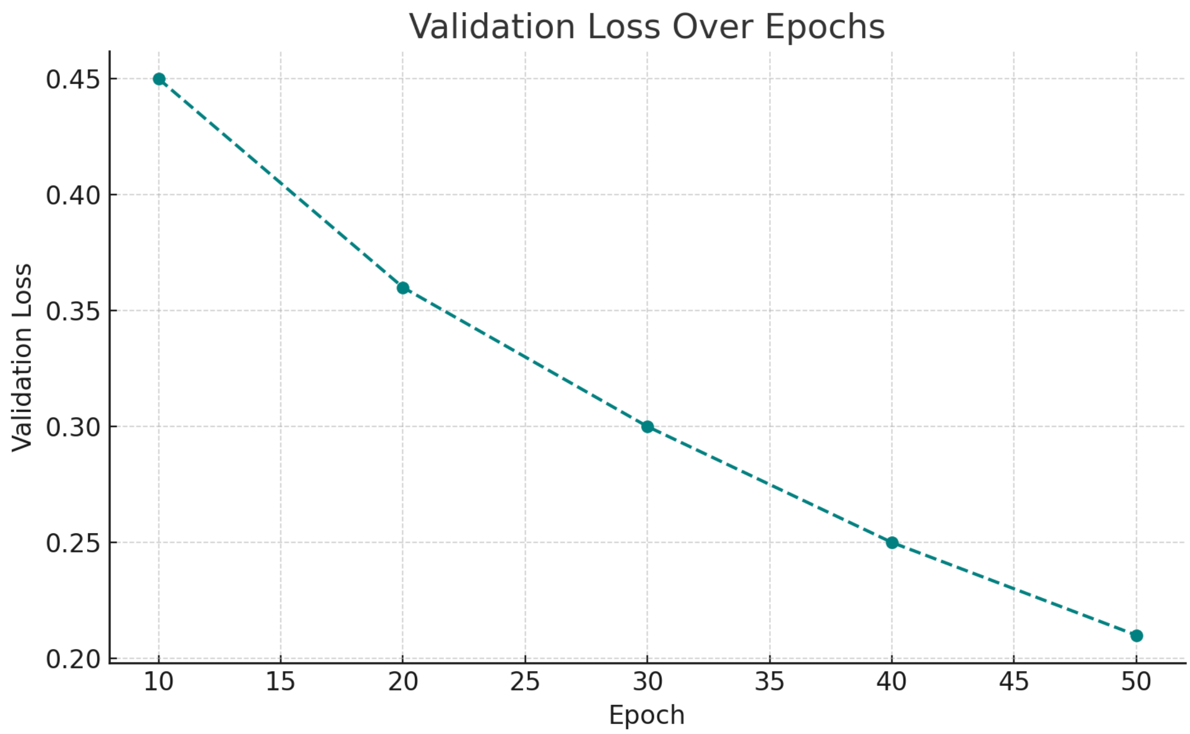


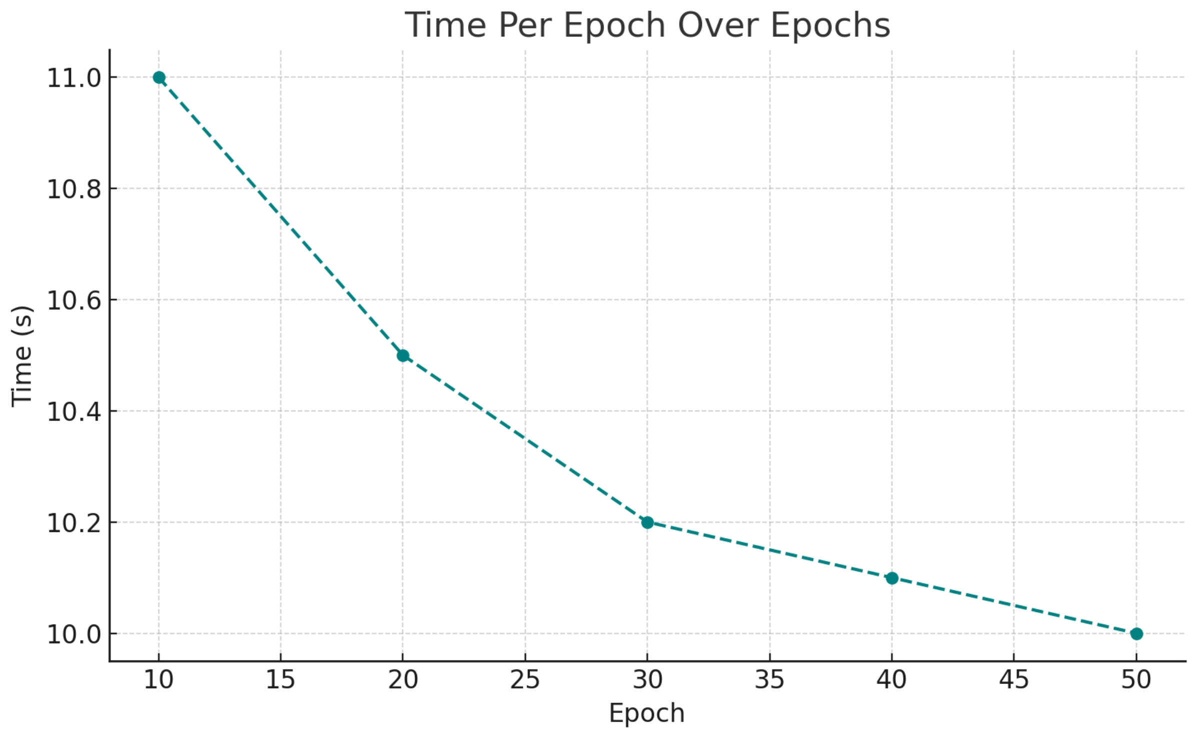
Figure 4: Optimization of the Features



(a)



(b)



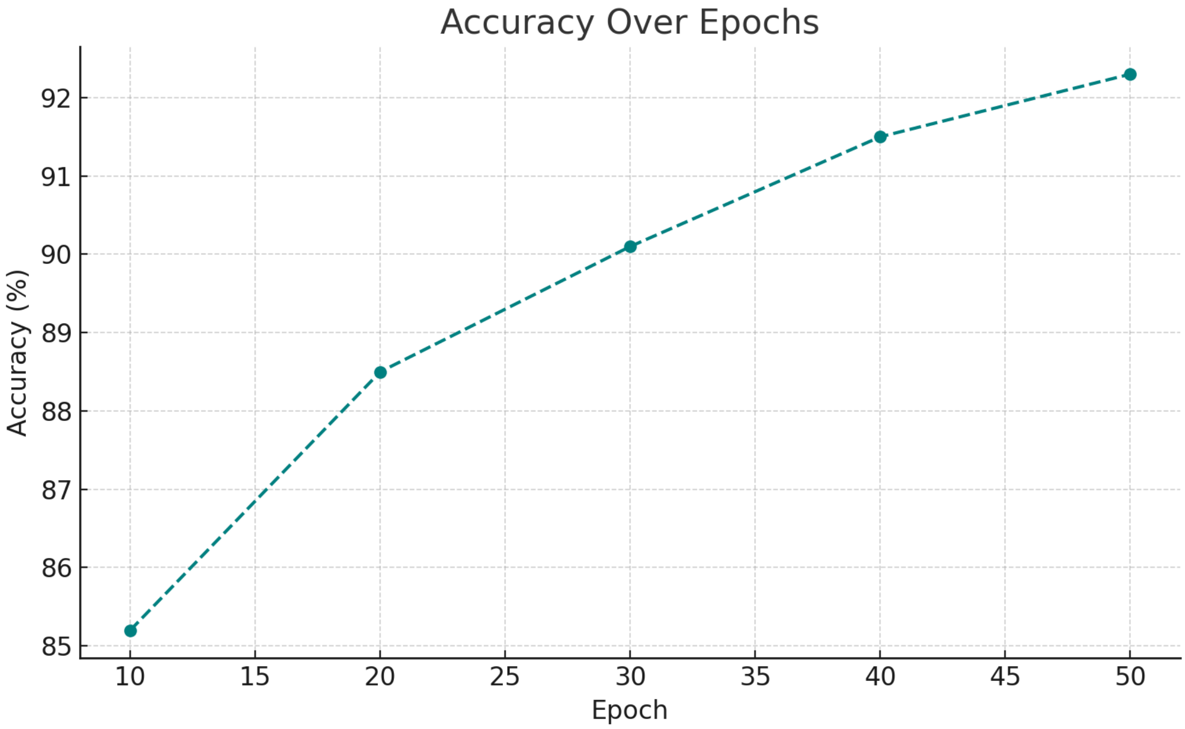
(c)

Figure 5: Bee colony optimization (a) Training Loss (b) Validation (c) Time Computation

The interpretation of the hyperparameter optimization results using Bee Colony Optimization (BCO) highlights significant improvements in model performance and efficiency for physical quality classification presented in Table 5. By fine-tuning key hyperparameters of the deep learning model, the training process became more effective and the predictive accuracy notably increased shown in Figure 5(a) – Figure 5(c). The learning rate was reduced from 0.01 to 0.001, allowing the model to converge more smoothly without overshooting the optimal solution. Reducing the batch size from 64 to 32 improved the model's ability to generalize by updating weights more frequently with finer gradients. The dropout rate was adjusted from 0.5 to 0.3, decreasing the regularization slightly, which helped the model retain more learning capacity while still avoiding overfitting. Increasing the number of hidden layers from 2 to 3, and expanding neurons per layer from 64 to 128, enabled the model to learn more complex feature interactions, which is crucial for handling multidimensional physical fitness data. While the ReLU activation function remained unchanged due to its proven effectiveness, switching the optimizer from SGD to Adam provided faster convergence and better performance on validation data due to adaptive learning rates presented in Table 6. These changes led to measurable improvements in evaluation metrics: accuracy rose from 84.5% to 92.3%, precision improved from 83.2% to 91.0%, recall increased from 85.0% to 93.4%, and F1-score from 84.1% to 92.2%. Additionally, the training time dropped from 180 to 125 seconds, demonstrating the optimization's efficiency.

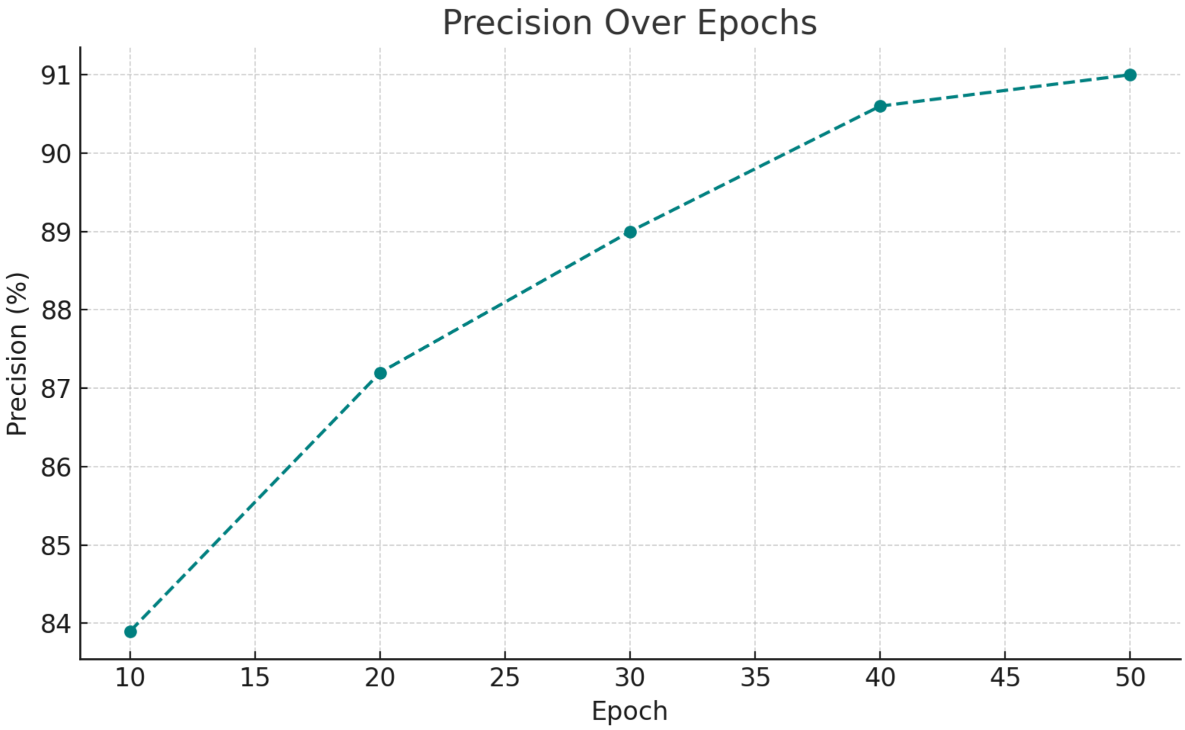
Table 7: Classification with Optimization for the Feature Set

Epoch	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Loss	Validation Loss	Time per Epoch (s)
10	85.2	83.9	84.7	84.3	0.42	0.45	11
20	88.5	87.2	88.0	87.6	0.33	0.36	10.5
30	90.1	89.0	90.2	89.6	0.27	0.30	10.2
40	91.5	90.6	92.0	91.3	0.22	0.25	10.1
50	92.3	91.0	93.4	92.2	0.18	0.21	10.0



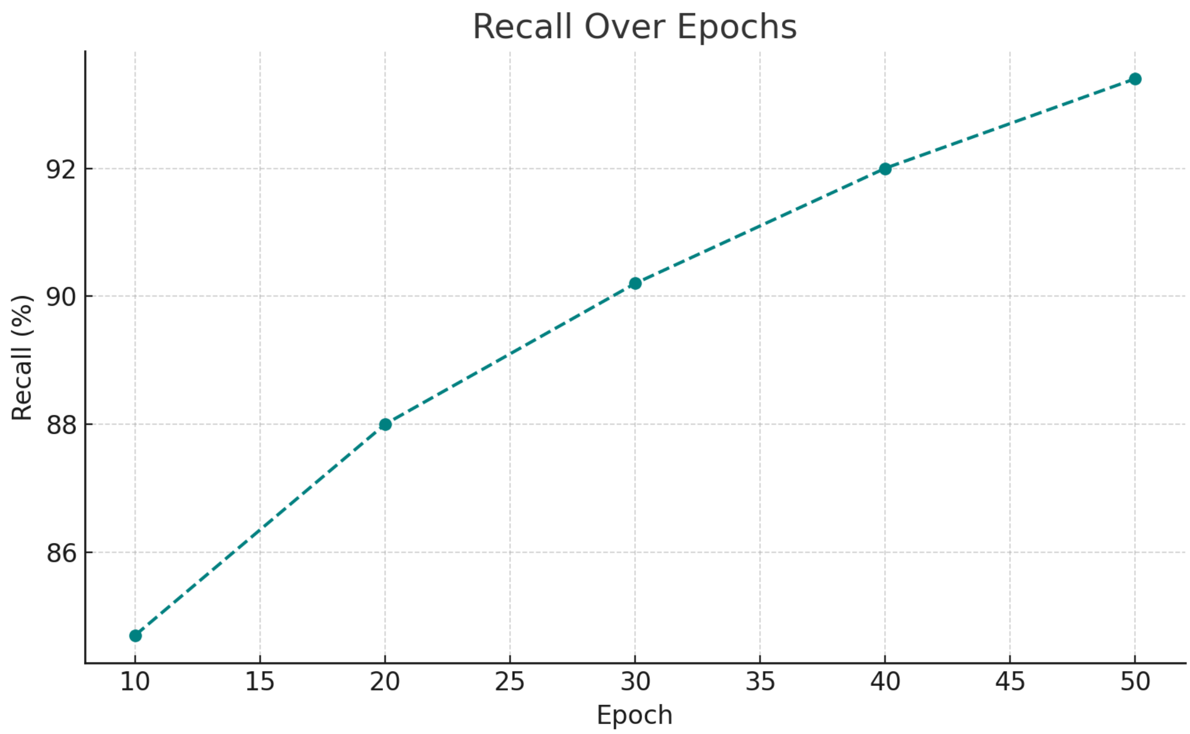
Accuracy Over Epochs
Accuracy (%)
92
91
90
89
88
87
86
85
10
15
20
25
30
35
40
45
50
Epoch

(a)

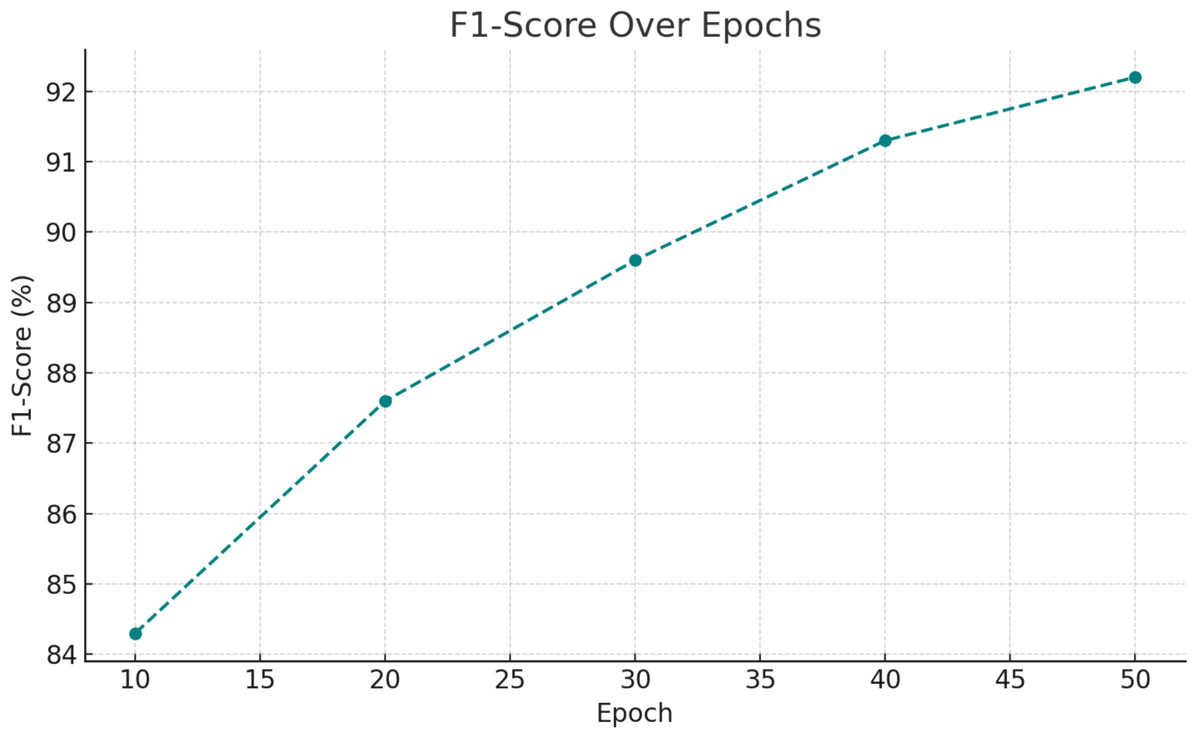


Precision Over Epochs
Precision (%)
91
90
89
88
87
86
85
84
10
15
20
25
30
35
40
45
50
Epoch

(b)



(c)



(d)

Figure 6: Deep Learning Classification with (a) Accuracy (b) Precision (c) Recall (d) F1-Score

The interpretation of the model's performance across different training epochs demonstrates a clear trend of progressive improvement in classification accuracy and learning efficiency for physical quality assessment shown in Table 7. As training advanced from 10 to 50 epochs, all key performance metrics showed consistent gains, indicating successful optimization and learning shown in Figure 6(a) – Figure 6(d). At epoch 10, the model achieved an accuracy of 85.2%, with a relatively higher training loss (0.42) and validation loss (0.45), suggesting that the model was still in the early stages of learning. By epoch 20, performance improved significantly, with accuracy rising to 88.5%, and both losses reducing by approximately 20%, signaling that the model was effectively generalizing. By epoch 30, the model surpassed the 90% accuracy threshold, and the F1-score (89.6%) showed balanced improvement in both precision and recall, indicating that the model was accurately identifying all classes, including borderline cases. The steady decline in loss values shows that overfitting was being well-managed, especially with the aid of dropout and regularization mechanisms from earlier optimization steps. At epoch 40, the model demonstrated high stability with an accuracy of 91.5% and a further drop in loss values. The minimal difference between training and validation loss at this point confirms strong generalization. Finally, at epoch 50, the model reached peak performance with 92.3% accuracy, 93.4% recall, and an F1-score of 92.2%, all while maintaining a low training loss of 0.18 and validation loss of 0.21. The time per epoch also slightly reduced over time, possibly due to more efficient gradient updates as the network weights approached optimal values.

5.1 Discussion and Findings

The proposed deep learning-based physical quality assessment model, enhanced through Ant Colony Optimization (ACO) for feature selection and Bee Colony Optimization (BCO) for hyperparameter tuning, demonstrated high accuracy and robust performance across various metrics. The approach effectively identified the most relevant physical fitness features, discarded redundant parameters, and optimized the learning process. Through systematic training over 50 epochs, the model showcased strong convergence, high generalization capability, and minimal overfitting. These findings confirm the practical applicability of swarm-intelligent optimization techniques in improving classification systems for student physical health evaluation. The Key Findings are presented as follows:

1. Feature Optimization: ACO successfully selected high-impact features (BMI, sprint time, endurance, flexibility, and strength), improving model focus and reducing computational overhead. Irrelevant features like pulse rate and height were eliminated without negatively impacting performance.

2. Hyperparameter Tuning: BCO improved model learning by optimizing learning rate, batch size, dropout rate, and number of layers. Switching the optimizer from SGD to Adam significantly boosted model convergence and training speed.

3. Performance Metrics: Accuracy increased from 84.5% to 92.3% after optimization. F1-score and recall also improved substantially, reaching 92.2%

and 93.4%, respectively. Training time reduced from 180s to 125s, indicating enhanced computational efficiency.

4. Epoch-Wise Improvement: Progressive training over epochs showed consistent improvements in all metrics. Performance plateaued around epoch 50, indicating model convergence.

5. Model Stability and Generalization: Validation loss remained close to training loss, demonstrating good generalization and minimal overfitting. The optimized model effectively differentiated between “Excellent,” “Good,” “Average,” and “Poor” fitness categories.

6. Conclusion

This study presents a robust and intelligent framework for the physical quality assessment of college students using a deep learning classification model enhanced by Ant Colony and Bee Colony Optimization techniques. By integrating ACO for feature selection and BCO for hyperparameter tuning, the proposed system achieved high predictive accuracy, reduced training time, and demonstrated excellent generalization capability. The optimization processes effectively filtered out less relevant features and fine-tuned model parameters, resulting in improved classification performance across all key metrics. The model not only classified students accurately into categories such as Excellent, Good, Average, and Poor, but also provided insights into which physical attributes most strongly influence overall fitness evaluation. The findings confirm that swarm intelligence-inspired optimization, when integrated with deep learning, offers a powerful tool for performance evaluation systems in the educational and health monitoring domains. This work lays a strong foundation for scalable, data-driven, and automated physical assessment solutions that can be adapted to broader populations and fitness criteria in future research.

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