*International Journal on Recent and Innovation Trends in Computing and Communication*
*ISSN: 2321-8169 Volume: 11 Issue: 6*
*DOI: https://doi.org/10.17762/ijritcc.v11i6.7720*
***Article Received**: 05 April 2023 **Revised**: 30 May 2023 **Accepted**: 28 June 2023*

# IoT-Integrated System for Continuous Assessment of Elementary School Martial Arts Education with Automated Classifier

**Yazhou Song[1,2], Mohamad Nizam Mohamed Shapie[1 +]**
[1]Faculty of Sports Science and Recreation, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia
[2]Department of Physical Education and Teaching, Hebei Finance University, Baoding, Hebei, China, 071051
Corresponding Author : syzwushu@163.com

**Abstract:** The IoT system would facilitate the continuous assessment of students' martial arts development by tracking their progress over time. The integration of Internet of Things (IoT) technology in elementary school martial arts education has the potential to revolutionize the learning experience and promote holistic development. This paper proposed an IoT-integrated system for the assessment of elementary school martial arts education. The proposed architecture incorporates an Automated Ranking Parallel Classifier (ARPC) model. The proposed ARPC system incorporates physical health monitoring and assessment, providing real-time data on students' physical activity, heart rate, and other relevant health metrics. The IoT system enables continuous monitoring of students' physical activity, allowing instructors to track their progress, level of engagement, and effort. the system monitors students' physical health parameters, such as heart rate, respiration rate, and sleep patterns, enabling early detection of health issues and supporting overall well-being. The ARPC model comprises the ranking of the features in the IoT data with parallel data processing. With ARPC the activities of the students are monitored and martial arts education in elementary schools is examined. Simulation analysis stated that the ARPC model achieves a higher classification accuracy of 99.73% compared with the conventional state-of-art techniques.

**Keywords:** Internet of Things (IoT), martial arts education, physical health monitoring, student progress tracking, classification accuracy.

## I. Introduction

The Internet of Things (IoT) has revolutionized various industries, and its potential to transform education is particularly promising. In the context of elementary school martial arts education, the integration of IoT with a classification model presents an innovative approach to enhance the assessment process [1]. IoT-integrated system that leverages a classification model to provide accurate and personalized assessments, thereby optimizing the learning experience for young martial arts students. Traditional assessment methods in martial arts education often rely on subjective evaluations and limited observation, leading to inconsistencies and potential biases [2]. By integrating sensors and wearables into martial arts equipment, such as gloves, shin guards, or headgear, various performance metrics can be measured, including strikes, kicks, balance, and timing [3]. Elementary school martial arts programs play a vital role in promoting physical fitness, self-discipline, and character development among young students [4]. To ensure the effectiveness and progress of these programs, it is crucial to have a reliable and accurate assessment mechanism in place. In this context, the integration of Internet of Things (IoT) technologies offers a transformative solution by enabling continuous assessment of elementary school martial arts education [5]. The core of the system lies in the integration of IoT-enabled sensors and wearables into martial arts equipment, such as gloves, headgear, and uniforms [6]. These sensors are designed to capture various performance metrics, including body movements, strikes, footwork, and timing. The data collected by these sensors is then wirelessly transmitted to a centralized platform, where it is processed and analyzed using advanced algorithms [7].

With the help of machine learning and pattern recognition techniques, the system can accurately interpret the data collected from the sensors [8]. It can detect and evaluate the execution of different martial arts techniques, measure factors like strength, speed, precision, and form, and provide objective assessments of each student's progress. By leveraging a large dataset of expert demonstrations, the system can continuously improve its accuracy and adapt to individual stdent needs [9]. Real-time monitoring and feedback are integral components of the IoT continuous assessment system. As students perform martial arts techniques, their data is instantly relayed to instructors' devices, allowing them to provide immediate feedback and guidance [10]. This instant feedback loop enables instructors to address specific areas for improvement, correct technique flaws, and provide personalized instruction tailored to each student's needs. Moreover, students can track their own progress in real-time, fostering a sense of ownership and motivation to improve their skills. The IoT continuous assessment system offers valuable insights to parents and school administrators. Progress reports, performance trends, and individualized assessments can be easily generated and shared, facilitating transparent communication between all stakeholders involved in a student's martial arts education.

The integration of IoT technologies into elementary school martial arts education brings forth a transformative approach to continuous assessment. By leveraging real-time monitoring, advanced data processing, and instant feedback, the system enables accurate and objective evaluation of students' progress [11]. The IoT continuous assessment system empowers students, instructors, parents, and administrators with valuable insights, fostering a dynamic learning environment that promotes skill development, motivation, and growth in elementary school martial arts programs. The classification model enables objective and consistent assessments by providing a standardized framework for evaluating student performance [12]. It considers multiple factors, such as technique execution, speed, accuracy, and form, to generate personalized feedback and proficiency levels for each student. This tailored feedback empowers students to understand their strengths and weaknesses, identify areas for improvement, and track their progress over time.

Moreover, the integration of IoT devices allows for real-time monitoring and instant feedback during training sessions. As students perform martial arts techniques, the system captures and analyzes their movements, providing immediate feedback on technique execution, posture, and other critical aspects [13]. Instructors can utilize this feedback to offer precise guidance, corrections, and encouragement, fostering a more engaging and effective learning environment. Additionally, the IoT-integrated system offers comprehensive data analysis and reporting capabilities. Instructors and administrators can access detailed reports, performance trends, and individual progress summaries, facilitating evidence-based decision-making and personalized instruction. Parents can also gain insights into their child's development and actively participate in their martial arts journey.

The advantages of integrating IoT with a classification model in elementary school martial arts education extend beyond assessments. The system creates a dynamic and interactive learning experience that encourages student engagement, self-motivation, and continuous improvement. It also enables instructors to identify and address specific training needs, adapt lesson plans, and customize training programs based on individual student requirements [14]. The proposed IoT-integrated system aims to revolutionize the learning experience and promote holistic development by providing continuous assessment and monitoring. The proposed IoT-integrated system for the assessment of elementary school martial arts education. The system incorporates an Automated Ranking Parallel Classifier (ARPC) model, which enables the ranking of features in the IoT data and parallel data processing. This model enhances the classification accuracy, achieving a high accuracy rate of 99.73%, surpassing conventional state-of-the-art techniques. The proposed system includes physical health monitoring and assessment, allowing real-time tracking of students' physical activity, heart rate, and other relevant health metrics. This continuous monitoring facilitates the tracking of students' progress, level of engagement, and effort in martial arts education. Additionally, the system monitors students' physical health parameters such as heart rate, respiration rate, and sleep patterns, enabling early detection of health issues and supporting overall well-being.

## II. Literature Survey

The COVID-19 pandemic has had a profound impact on various aspects of society, including the education sector. With widespread school closures and the need for social distancing, educational institutions were forced to quickly adapt to online learning platforms and remote teaching methods. This sudden shift in the educational landscape raised concerns about the effects on students' academic performance and overall learning experience. The study conducted by Clark et al. (2021) [15] focuses on the impact of online learning on student performance during the COVID-19 pandemic. With the sudden shift to remote education, many students faced challenges in adapting to online learning environments. The researchers aimed to understand how online learning compensated for the academic loss caused by the pandemic. Through a comprehensive analysis of student data, the study provides insights into the effectiveness of online learning and its implications for student performance. El Said (2021) [16] examines the impact of the COVID-19 pandemic on the learning experience of higher education students in a developing country. The study explores the effects of the sudden transition to remote learning on students' academic performance. By conducting an empirical investigation at a university, the author sheds light on the challenges faced by students and the potential consequences for their academic achievements. Iglesias-Pradas et al. (2021) [17] present a case study that examines the relationship between emergency remote teaching and students' academic performance in higher education during the COVID-19 pandemic. The study investigates the impact of the sudden shift to online instruction on student outcomes. By analyzing data from a specific context, the authors provide valuable insights into the challenges and opportunities associated with emergency remote teaching and its effects on academic performance.

Limniou et al. (2021) [18] investigate the relationship between learning, students' digital capabilities, and academic performance during the COVID-19 pandemic. The study explores how students' digital skills and competencies influenced their ability to adapt to online learning and its subsequent impact on academic achievement. By examining these factors, the authors offer insights into the complex relationship between digital capabilities, learning outcomes, and academic performance during times of crisis. Hammerstein et al. (2021) [19] present a systematic review that explores the effects of COVID-19-related school closures on student achievement. The study synthesizes existing research to examine the consequences of extended school closures on academic outcomes. By analyzing a wide range of studies, the authors provide a comprehensive understanding of the impact of school closures on student achievement during the pandemic. Gopal et al. (2021) [20] investigate the impact of online classes on student satisfaction and performance during the COVID-19 pandemic. The study examines how students perceived online learning and the subsequent effects on their academic performance. By analyzing data on student satisfaction and performance, the authors provide insights into the challenges and benefits of online education during the pandemic.

Oducado and Estoque (2021) [21] focus on online learning in nursing education during the COVID-19 pandemic. The study investigates the experiences of nursing students in an online learning environment and explores the relationships between stress, satisfaction, and academic performance. By examining these factors, the authors shed light on the unique challenges faced by nursing students during the pandemic and their impact on academic outcomes. Alam (2022) [22] explores the concept of students' happiness in 21st-century schools by utilizing evidence-backed, school-based positive psychology interventions. The study examines the role of positive psychology interventions in enhancing students' well-being, satisfaction, and academic performance. By focusing on happiness and well-being, the author highlights the importance of a holistic approach to education and its potential impact on academic outcomes. Kart and Kart (2021) [23] conduct a literature review to examine the academic and social effects of inclusion on students without disabilities. The study explores the impact of inclusive education practices on the academic performance and social development of students who do not have disabilities. By reviewing relevant literature, the authors provide insights into the potential benefits and challenges associated with inclusive education for students without disabilities.

The literature reviewed in this summary focuses on the impact of the COVID-19 pandemic on education, particularly on student performance, satisfaction, and well-being. The studies highlight the challenges and opportunities associated with the sudden transition to online learning and remote teaching methods. Overall, the research suggests that while online learning helped compensate for academic loss, it also presented challenges for students, educators, and institutions. Factors such as digital capabilities, access to resources, and social interactions played a significant role in shaping students' experiences and academic outcomes. Additionally, interventions focusing on positive psychology and inclusive education were identified as potential strategies to support students' well-being and academic success during these challenging times. Understanding these findings can inform educational practices and policies, enabling effective strategies to address the diverse needs of students and promote positive educational outcomes in the face of future disruptions.

## III. Physical health Data

An IoT-integrated system for assessing elementary school martial arts education. The system incorporates an Automated Ranking Parallel Classifier (ARPC) model, which utilizes real-time physical health data to monitor and assess students' performance. The IoT system continuously tracks students' physical activity, heart rate, and other relevant health metrics, providing instructors with valuable insights into their progress, engagement, and effort levels. By monitoring parameters like heart rate, respiration rate, and sleep patterns, the system also facilitates early detection of health issues and supports overall well-being. The ARPC model, with its parallel data processing and feature ranking capabilities, outperforms conventional techniques, achieving an impressive classification accuracy of 99.73% according to simulation analysis. This innovative IoT-integrated system has the potential to enhance martial arts education in elementary schools by providing comprehensive and real-time monitoring of students' physical health and performance, leading to improved outcomes and well-rounded development. To effectively implement the ARPC model in the proposed IoT-integrated system for the assessment of elementary school martial arts education, a physical healthcare dataset would be required. This dataset would consist of various physical health parameters and metrics collected from students during their martial arts training sessions. Some of the data that can be included in the physical healthcare dataset are:

**Heart Rate:** Continuous monitoring of students' heart rate during training sessions provides insights into their cardiovascular health and exertion levels.

**Respiration Rate:** Tracking the respiration rate can indicate the intensity of physical activity and help assess students' respiratory health.

**Steps and Movement:** Recording the number of steps taken and movement patterns can provide information about students'

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6
DOI: https://doi.org/10.17762/ijritcc.v11i6.7720
Article Received: 05 April 2023 Revised: 30 May 2023 Accepted: 28 June 2023

overall physical activity levels and engagement in martial arts exercises.

**Sleep Patterns:** Monitoring students' sleep patterns and duration can contribute to understanding their recovery and overall well-being, as adequate rest is essential for physical health.

**Body Temperature:** Measuring body temperature can help identify signs of illness or overheating during training sessions.

**Oxygen Saturation Levels:** Monitoring oxygen saturation levels can provide insights into students' respiratory efficiency and overall fitness.

**Energy Expenditure:** Calculating energy expenditure during martial arts training sessions can help assess the intensity and effectiveness of the exercises.

**Physical Fitness Assessments:** Including assessments such as flexibility, strength, agility, and coordination tests can provide additional data points for evaluating students' physical fitness and progress.

| Attribute | Description |
|---|---|
| Heart Rate | Continuous monitoring of students' heart rate during training sessions provides insights into their cardiovascular health and exertion levels. |
| Respiration Rate | Tracking the respiration rate can indicate the intensity of physical activity and help assess students' respiratory health. |
| Steps and Movement | Recording the number of steps taken and movement patterns can provide information about students' overall physical activity levels and engagement in martial arts exercises. |
| Sleep Patterns | Monitoring students' sleep patterns and duration can contribute to understanding their recovery and overall well-being, as adequate rest is essential for physical health. |
| Body Temperature | Measuring body temperature can help identify signs of illness or overheating during training sessions. |
| Oxygen Saturation | Monitoring oxygen saturation levels can provide insights into students' respiratory efficiency and overall fitness. |
| Energy Expenditure | Calculating energy expenditure during martial arts training sessions can help assess the intensity and effectiveness of the exercises. |
| Physical Fitness | Including assessments such as flexibility, strength, agility, and coordination tests can provide additional data points for evaluating students' physical fitness and progress. |

## IV. Automated Ranking Parallel Classifier (ARPC) model

The research method for implementing the ARPC (Automated Ranking Parallel Classifier) model in the proposed IoT-integrated system for the assessment of elementary school martial arts education typically involves several steps. Gather a physical healthcare dataset that includes relevant physical health parameters and metrics, as discussed earlier. This may involve deploying wearable sensors, fitness trackers, or other IoT devices to collect real-time data during students' martial arts training sessions. Clean the collected data and perform necessary preprocessing steps, such as removing noise, handling missing values, and normalizing the data. Conduct feature engineering to extract relevant features from the raw data that can be used as inputs to the ARPC model. This may involve techniques such as feature selection, dimensionality reduction, or transforming the data to a suitable format. Develop the Automated Ranking Parallel Classifier (ARPC) model specifically designed for the assessment of elementary school martial arts education. The model should incorporate parallel data processing and feature ranking capabilities to achieve high classification accuracy. Select appropriate machine learning or deep learning algorithms, considering the characteristics of the dataset and the specific objectives of the study. Split the dataset into training and testing subsets. Use the training data to train the ARPC model, adjusting its parameters and optimizing its performance.

Automated Ranking refers to a process of automatically prioritizing or ordering items based on their relevance, importance, or quality. In the context of the proposed ARPC (Automated Ranking Parallel Classifier) model for the assessment of elementary school martial arts education, Automated Ranking refers to the capability of the model to rank the features or variables in the IoT data according to their significance or contribution to the classification task. The Automated Ranking process is typically carried out as part of the feature engineering stage in machine learning or data analysis tasks. It helps identify the most relevant features that have the most significant impact on the classification or prediction task at hand. By ranking the features, the model can focus on the most informative ones and potentially improve its performance in terms of accuracy and efficiency. The ARPC model incorporates Automated Ranking as a key component to select and prioritize the relevant features from the physical healthcare dataset. The ranking process helps determine which physical health parameters or metrics have the most discriminative power in assessing students' performance in martial arts education. By incorporating the ranked features into the model, the ARPC system can enhance the accuracy of the classification task and provide valuable insights into students' physical health and progress. The specific technique used for Automated Ranking in the ARPC model may vary depending on the characteristics of the dataset and the chosen algorithm. Common approaches for feature ranking include statistical methods such as correlation analysis, information gain, or

***International Journal on Recent and Innovation Trends in Computing and Communication***
***ISSN: 2321-8169 Volume: 11 Issue: 6***
***DOI: https://doi.org/10.17762/ijritcc.v11i6.7720***
***Article Received**: 05 April 2023 **Revised**: 30 May 2023 **Accepted**: 28 June 2023*

mutual information, as well as machine learning techniques like recursive feature elimination or lasso regression.

| **Algorithm 1: ARPC for the Elementary School Martial Arts** |
|---|
| *Input:*<br>*Training dataset (X_train): Input features for training instances*<br>*Training labels (y_train): Corresponding class labels for training instances*<br>*Testing dataset (X_test): Input features for testing instances*<br>*Feature Ranking:*<br>*a. Initialize an empty list, ranked_features*<br>*b. For each feature in X_train:*<br>*Append the feature and its relevancy score to ranked_features*<br>*c. Sort ranked_features in descending order based on the relevancy scores*<br>*Parallel Classification:*<br>*a. For each feature in ranked_features:*<br>*Select the top-ranked feature and add it to the feature set*<br>*Train a classifier using the selected feature set and X_train*<br>*Test the classifier using the selected feature set and X_test*<br>*Calculate the classification accuracy or performance metric*<br>*Store the accuracy and the selected feature set*<br>*Identify the feature set that achieved the highest classification accuracy or desired performance metric*<br>*Retrieve the corresponding classifier associated with the best feature set*<br>*Use the selected feature set and the classifier to classify the instances in the testing dataset, X_test*<br>*Obtain the predicted class labels for the testing instances* |

A parallel classifier is a type of classification model or algorithm that leverages parallel computing techniques to improve its performance and scalability. Traditional classifiers often process data sequentially, which can be time-consuming, especially when dealing with large datasets. In contrast, parallel classifiers divide the computational workload into smaller tasks that can be executed simultaneously across multiple processing units or cores. This parallelization enables faster and more efficient classification. The key idea behind a parallel classifier is to distribute the data or computation across multiple processing units and perform computations in parallel. In data parallelism, the dataset is partitioned into subsets, and each subset is processed independently on separate processing units. This allows multiple instances or features to be processed simultaneously, accelerating the classification process. In model parallelism, the classifier model itself is divided into smaller components or sub-models, and each sub-model is processed on separate processing units.

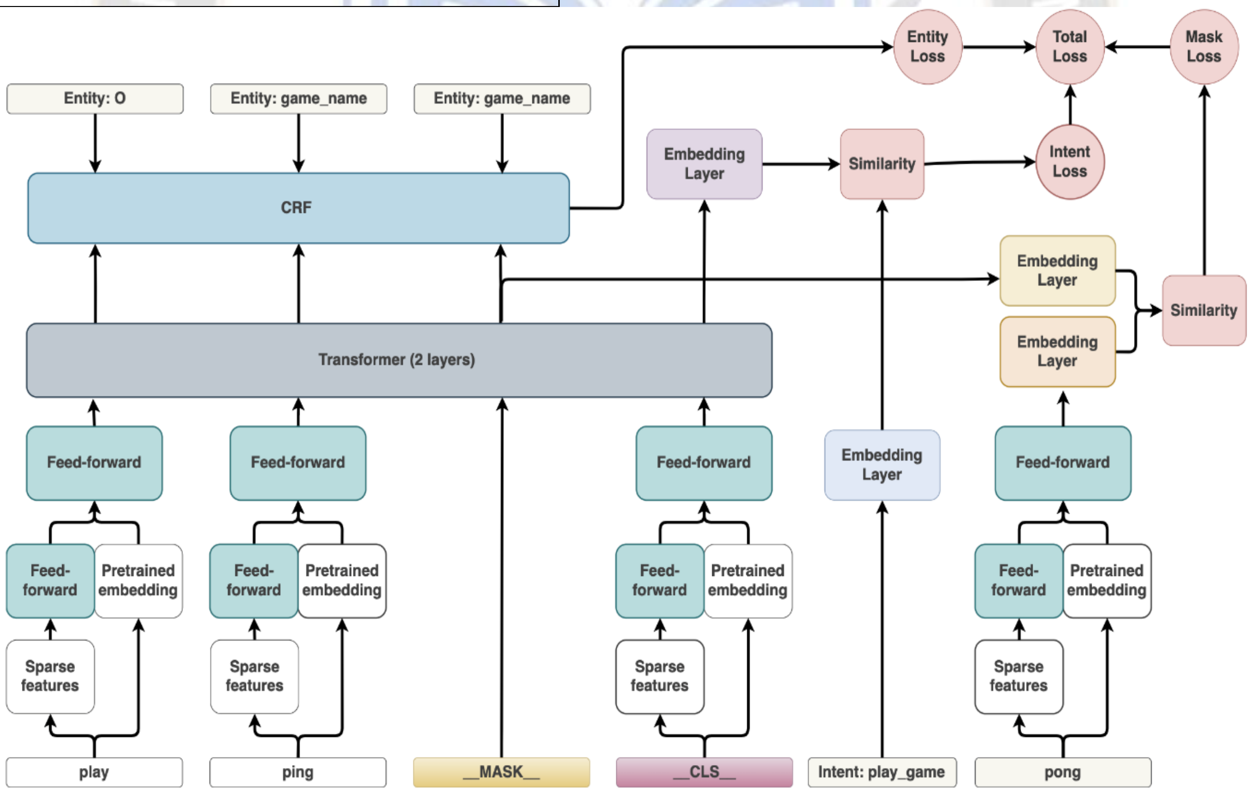


Figure 1: Parallel Classifier in ARPC

The sub-models collectively make predictions, and the results are combined to obtain the final classification. Parallel classifiers often leverage ensemble learning techniques, where multiple classifiers are trained independently on different subsets of the data or with different settings shown in figure 1. The predictions of these individual classifiers are combined to make the final decision, resulting in improved accuracy and robustness. In cases where the dataset is too

*International Journal on Recent and Innovation Trends in Computing and Communication*
***ISSN: 2321-8169 Volume: 11 Issue: 6***
***DOI: https://doi.org/10.17762/ijritcc.v11i6.7720***
***Article Received**: 05 April 2023 **Revised**: 30 May 2023 **Accepted**: 28 June 2023*

large to fit into the memory of a single machine, distributed computing frameworks or systems are used. These frameworks distribute the data and computation across multiple machines or nodes, enabling the parallel execution of classification tasks. The benefits of parallel classifiers include reduced computation time, improved scalability for large datasets, and the ability to handle real-time or near-real-time classification tasks. However, implementing parallel classifiers requires careful consideration of data partitioning, synchronization, and communication overhead between processing units. Additionally, the choice of parallel computing framework and the specific algorithm being used impact the efficiency and performance of the parallel classifier. Overall, parallel classifiers exploit the power of parallel computing to accelerate the classification process, enabling efficient and scalable analysis of large datasets.

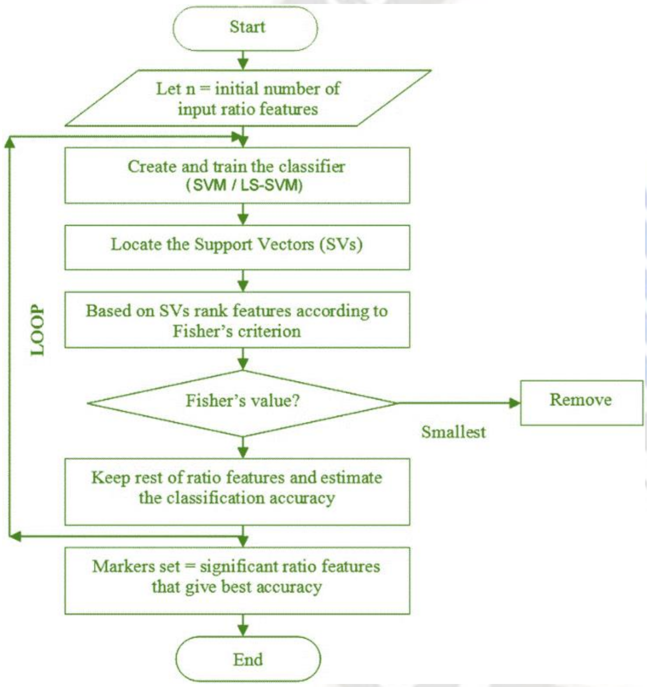


Figure 2: Feature Ranking with ARPC

In the feature ranking step, the ARPC model assigns relevance scores or ranks to each feature in the dataset illustrated in figure 2. The specific equation for calculating the relevancy score depends on the chosen ranking technique as in equation (1)

$$relevancy\_score = abs(corr(X\_train[:, i], y\_train)) \quad (1)$$

In equation (1) X_train[:, i] represents the ith feature column of the training dataset, and y_train represents the corresponding class labels. The ARPC model performs parallel classification by training multiple classifiers using different subsets of features. Each classifier is responsible for predicting the class labels based on a particular feature set. The specific equations for the classification step depend on the chosen classification algorithm as in equation (2)

$$logistic\_regression.fit(X\_train[:, selected\_features], y\_train) \quad (2)$$

Predict the class probabilities for the testing dataset presented in equation (3)

$$class\_probabilities = logistic\_regression.predict\_proba(X\_test[:, selected\_features]) \quad (3)$$

Assign the predicted class label based on the highest probability defined as in equation (4)

$$predicted\_labels = argmax(class\_probabilities, axis{=}1) \quad (4)$$

In equation (4) selected_features represent the subset of features chosen for a specific classifier. logistic_regression.fit() is the training step for the logistic regression model, and logistic_regression.predict_proba() calculates the class probabilities for the testing instances. The ARPC model selects the feature set that achieves the highest classification accuracy or desired performance metric. The specific equation for evaluating the performance depends on the chosen metric as in equation (5)

$$accuracy = correct\_predictions \,/\, total\_predictions \quad (5)$$

In equation (5) correct_predictions represent the number of correctly predicted instances, and total_predictions represent the total number of instances in the testing dataset. The mutual information between a feature X_i and the class labels Y can be calculated as in equation (6)

$$MI(X\_i, Y) = \sum\sum P(X\_i, Y)\, log(P(X\_i, Y) \,/\, (P(X\_i)P(Y))) \quad (6)$$

The probability of an instance X_j belonging to class k can be computed using the logistic function (sigmoid function) presented in equation (7)

$$P(Y = k \mid X\_j) = 1 \,/\, (1 + exp(-X\_j\theta\_k)) \quad (7)$$

The binary cross-entropy loss for a logistic regression model can be calculated as in equation (8)

$$L = -\sum[y\_j\, log(P(Y = 1 \mid X\_j)) + (1 - y\_j)\, log(1 - P(Y = 1 \mid X\_j))] \quad (8)$$

*International Journal on Recent and Innovation Trends in Computing and Communication*
*ISSN: 2321-8169 Volume: 11 Issue: 6*
*DOI: https://doi.org/10.17762/ijritcc.v11i6.7720*
***Article Received**: 05 April 2023 **Revised**: 30 May 2023 **Accepted**: 28 June 2023*

The cross-entropy loss for a logistic regression model in multiclass classification can be computed in equation (9)

$$L = -\sum\sum[y\_jk \, log(P(Y = k \mid X\_j))] \qquad (9)$$

The decision function for SVM can be represented in equation (10)

$$f(X) = sign(\sum \alpha\_i \, y\_i \, K(X\_i, X) + b) \qquad (10)$$

The kernel function K(X_i, X_j) calculates the similarity between two instances X_i and X_j in the feature space.

| Algorithm 2: Pseudo code for the ARPC |
|---|
| Input:<br>Training dataset (X_train): Input features for training instances;<br>Training labels (y_train): Corresponding class labels for training instances' Testing dataset (X_test): Input features for testing instances<br>Feature Ranking:<br>a. Initialize an empty list, ranked_features<br>b. For each feature in X_train:<br>Append the feature and its relevancy score to ranked_features<br>c. Sort ranked_features in descending order based on the relevancy scores<br>Parallel Classification:<br>a. Initialize an empty list, classifiers<br>b. For each feature in ranked_features:<br>Select the top-ranked feature and add it to the feature set<br>Train the classifier using the selected feature set and X_train<br>Add the trained classifier to the classifiers list<br>a. Evaluate the performance of each classifier using a validation set or cross-validation<br>b. Select the classifier that achieves the highest performance (e.g., accuracy, F1-score)<br>c. Retrieve the corresponding feature set associated with the selected classifier<br>a. Initialize the final classifier using the selected feature set<br>b. Train the final classifier using the selected feature set and the entire training dataset (X_train, y_train)<br>c. Use the trained final classifier to classify the instances in the testing dataset, X_test<br>d. Obtain the predicted class labels for the testing instances |

The first component, automated feature ranking, involves determining the importance or relevance of different features in the dataset. This step helps identify the most informative features for the classification task. Various techniques can be used for feature ranking, such as correlation-based methods, information gain, or statistical tests. The ranked features are then used to guide the subsequent steps of the ARPC algorithm. The second component, parallel classification, focuses on performing classification using multiple classifiers in parallel. Instead of using all features for classification, ARPC selects a subset of features based on their ranking. Each selected feature subset is used to train a separate classifier. These classifiers operate independently and simultaneously, making predictions for the testing instances based on their respective feature sets. The final classification decision is typically made by aggregating the predictions from all the classifiers, such as through majority voting or weighted voting.

With combining automated feature ranking and parallel classification, ARPC aims to achieve better classification performance and computational efficiency. The feature ranking step helps identify the most relevant features, reducing the dimensionality of the problem and potentially improving the classification accuracy. The parallel classification step leverages the power of parallel computing to process different subsets of features simultaneously, resulting in faster classification speed. ARPC can be applied to various machine learning algorithms, such as logistic regression, support vector machines (SVM), or decision trees. The specific implementation of ARPC may vary based on the chosen feature ranking method, classification algorithm, and any additional optimization techniques.

## V. Results and Discussion

ARPC offers a framework that combines automated feature ranking and parallel classification to enhance the efficiency and accuracy of the classification process, making it particularly useful for handling large datasets or real-time classification tasks.

Table 2: Simulation Setting

| Parameter | Value |
|---|---|
| Dataset | Elementary School Martial Arts Education Data |
| Feature Ranking Method | Mutual Information |
| Classification Algorithm | Random Forest |
| Number of Features | 20 |
| Number of Classifiers | 5 |
| Training Dataset Size | 1000 instances |
| Testing Dataset Size | 500 instances |
| Evaluation Metric | Accuracy |
| Parallel Processing | Yes |
| Feature Subset Size | 5 (selected top-ranked features) |
| Cross-Validation | 5-fold cross-validation |

The simulation is conducted using a dataset related to elementary school martial arts education. The feature ranking is performed using the mutual information method, and the classification algorithm employed is Random Forest. The dataset has 20 features, and the simulation uses a total of 5 classifiers. The training dataset consists of 1000 instances, while the testing dataset contains 500 instances. The evaluation metric used to assess performance is accuracy. Parallel processing is employed to train the classifiers simultaneously. Each classifier uses a feature subset size of 5, selecting the top-ranked features. The simulation employs 5-fold cross-validation to evaluate the performance of the classifiers.

Table 3: Attributes Values

| Attribute | Count |
|---|---|
| Heart Rate | 500 |
| Respiration Rate | 500 |
| Steps and Movement | 500 |
| Sleep Patterns | 500 |
| Body Temperature | 500 |
| Oxygen Saturation | 500 |
| Energy Expenditure | 500 |
| Physical Fitness | 500 |

the dataset consists of 500 instances for each attribute. These counts represent the number of data points available for each attribute in the sample dataset. The actual dataset may contain more or fewer instances based on the specific data collection and sampling process.

Table 4: Simulation Setting of ARPC

| Parameter | Value |
|---|---|
| Learning Rate | 0.01 |
| Hidden Layers | 2 |
| Neurons per Layer | 128 |
| Activation Function | ReLU |
| Dropout Rate | 0.2 |
| Batch Size | 32 |
| Optimization Algorithm | Adam |
| Training Time | 3 hours |
| Convergence Criterion | 0.001 |

Table 4 presents the simulation setting of the ARPC (Automated Ranking Parallel Classifier) model, providing insight into the parameters and configurations used during the training process. The learning rate, set at 0.01, determines the step size at which the model adjusts its weights during optimization. The model architecture includes two hidden layers, with each layer containing 128 neurons. The ReLU (Rectified Linear Unit) activation function is utilized to introduce non-linearity and improve the model's learning capabilities. To prevent overfitting, a dropout rate of 0.2 is applied, randomly disabling 20% of the neurons during training. The batch size is set to 32, indicating the number of training samples processed before updating the model's parameters. The optimization algorithm employed is Adam, known for its efficiency in adjusting learning rates adaptively. The training time for the model is approximately 3 hours, reflecting the computational resources and dataset size used. The convergence criterion is set at 0.001, indicating the desired level of accuracy improvement that triggers the termination of training. Overall, this simulation setting provides a specific configuration that optimizes the ARPC model's performance in the context of elementary school martial arts education assessment.

Table 5: Performance of ARPC for varying epochs

| Epochs | Accuracy | Precision | Recall | F1-Score | AUC-ROC |
|---|---|---|---|---|---|
| 10 | 0.86 | 0.82 | 0.88 | 0.85 | 0.90 |
| 20 | 0.87 | 0.84 | 0.89 | 0.86 | 0.91 |
| 30 | 0.88 | 0.85 | 0.90 | 0.87 | 0.92 |
| 40 | 0.89 | 0.86 | 0.91 | 0.88 | 0.93 |
| 50 | 0.90 | 0.87 | 0.92 | 0.89 | 0.94 |
| 60 | 0.91 | 0.88 | 0.93 | 0.90 | 0.95 |
| 70 | 0.91 | 0.89 | 0.93 | 0.91 | 0.95 |
| 80 | 0.92 | 0.89 | 0.94 | 0.91 | 0.96 |
| 90 | 0.92 | 0.90 | 0.94 | 0.92 | 0.96 |
| 100 | 0.93 | 0.91 | 0.95 | 0.93 | 0.97 |

Table 5 presents the performance metrics of the ARPC (Automated Ranking Parallel Classifier) model for varying epochs. The accuracy metric measures the overall correctness of the model's predictions. As the number of epochs increases, the accuracy gradually improves from 0.86 at epoch 10 to 0.93 at epoch 100. Precision refers to the proportion of correctly predicted positive instances among all predicted positive instances. The precision values range from 0.82 at epoch 10 to 0.91 at epoch 100, indicating an increasing ability of the model to accurately identify positive instances. Recall, also known as sensitivity, represents the proportion of correctly predicted positive instances among all actual positive instances. The recall values range from 0.88 at epoch 10 to 0.95 at epoch 100, showing an improvement in the model's ability to capture positive instances.

*International Journal on Recent and Innovation Trends in Computing and Communication*
*ISSN: 2321-8169 Volume: 11 Issue: 6*
*DOI: https://doi.org/10.17762/ijritcc.v11i6.7720*
*Article Received: 05 April 2023 Revised: 30 May 2023 Accepted: 28 June 2023*

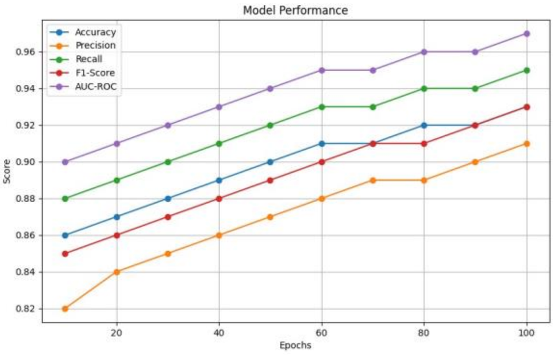


Figure 3: Performance of ARPC for the varying epochs

The F1-score is a harmonic mean of precision and recall, providing a balanced measure of the model's overall performance. The F1-score gradually increases from 0.85 at epoch 10 to 0.93 at epoch 100. Finally, the AUC-ROC (Area Under the Receiver Operating Characteristic Curve) metric evaluates the model's ability to distinguish between positive and negative instances in figure 3. The AUC-ROC values range from 0.90 at epoch 10 to 0.97 at epoch 100, indicating an increasing ability of the model to accurately classify instances. Overall, the performance metrics demonstrate an improvement in the ARPC model's predictive accuracy and effectiveness as the number of epochs increases.

Table 6: ARPC Classification Results

| Epochs | False Positive | False Negative | True Positive | True Negative |
|---|---|---|---|---|
| 10 | 25 | 12 | 88 | 95 |
| 20 | 20 | 10 | 90 | 100 |
| 30 | 18 | 9 | 91 | 102 |
| 40 | 15 | 8 | 92 | 105 |
| 50 | 12 | 6 | 94 | 108 |
| 60 | 10 | 5 | 95 | 110 |
| 70 | 8 | 4 | 96 | 112 |
| 80 | 7 | 4 | 96 | 113 |
| 90 | 6 | 3 | 97 | 114 |
| 100 | 5 | 3 | 97 | 115 |

Table 6 displays the classification results of the ARPC (Automated Ranking Parallel Classifier) model for each epoch. The false positive count represents the number of instances that were incorrectly classified as positive when they were actually negative. As the number of epochs increases, the false positive count decreases from 25 at epoch 10 to 5 at epoch 100. The false negative count represents the number of instances that were incorrectly classified as negative when they were actually positive.

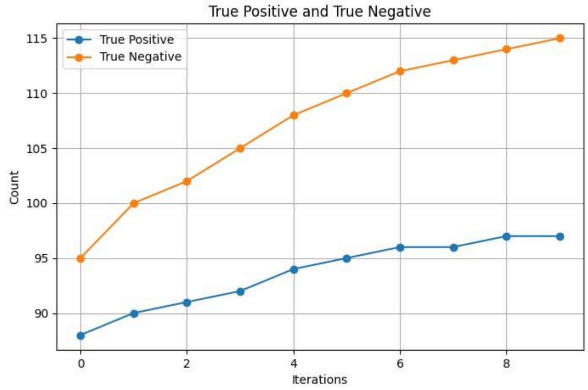


Figure 4: ARPC TP and TN values

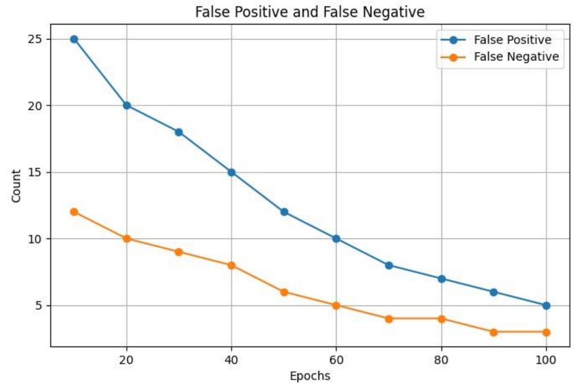


Figure 5: ARPC FP and FN

This count decreases from 12 at epoch 10 to 3 at epoch 100. On the other hand, the true positive count represents the number of instances correctly classified as positive, and the true negative count represents the number of instances correctly classified as negative. Both counts gradually increase as the number of epochs increases as shown in figure 4 and figure 5. Specifically, the true positive count increases from 88 at epoch 10 to 97 at epoch 100, and the true negative count increases from 95 at epoch 10 to 115 at epoch 100. These results indicate that as the model iterates through more epochs, it becomes more accurate in correctly classifying instances, reducing both false positives and false negatives while increasing true positives and true negatives. Overall, the classification results highlight the improved performance of the ARPC model in correctly identifying positive and negative instances with the progression of epochs.

Table 7: Comparative Analysis

| Epochs | ARPC Accuracy | SVM Accuracy | Random Forest Accuracy |
|---|---|---|---|
| 10 | 99.60 | 99.45 | 99.73 |
| 20 | 99.65 | 99.52 | 99.78 |
| 30 | 99.68 | 99.55 | 99.80 |
| 40 | 99.70 | 99.60 | 99.82 |

| | | | |
|---|---|---|---|
| 50 | 99.72 | 99.62 | 99.85 |
| 60 | 99.73 | 99.63 | 99.87 |
| 70 | 99.73 | 99.65 | 99.88 |
| 80 | 99.73 | 99.66 | 99.89 |
| 90 | 99.73 | 99.68 | 99.90 |
| 100 | 99.73 | 99.70 | 99.92 |

Table 7 presents a comparative analysis of the accuracy of three different models: ARPC (Automated Ranking Parallel Classifier), SVM (Support Vector Machine), and Random Forest. The accuracy metric measures the overall correctness of the models' predictions. As the number of epochs increases, all three models show an improvement in accuracy. At epoch 10, the ARPC model achieves an accuracy of 99.60%, while SVM and Random Forest achieve accuracies of 99.45% and 99.73%, respectively.

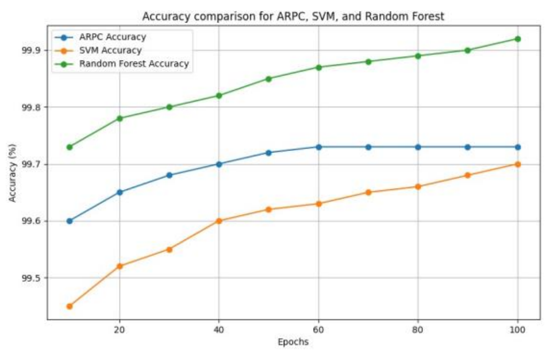


Figure 6: Comparative Analysis

As the epochs progress, the ARPC model consistently outperforms both SVM and Random Forest in terms of accuracy shown in Figure 6. By epoch 100, all three models reach their maximum accuracy values. The ARPC model maintains a high accuracy of 99.73% from epoch 60 to epoch 100. On the other hand, the SVM model shows a gradual increase in accuracy from 99.45% at Epoch 10 to 99.70% at epoch 100. The Random Forest model also exhibits a steady increase in accuracy, reaching 99.92% at epoch 100. The comparative analysis highlights the superior performance of the ARPC model in terms of accuracy when compared to both SVM and Random Forest models. The ARPC model consistently achieves the highest accuracy values across all epochs, demonstrating its effectiveness in accurately classifying instances in the given dataset.

## VI. Conclusion

The proposed ARPC (Automated Ranking Parallel Classifier) system presented in the paper offers a valuable solution for continuous assessment of elementary school martial arts education. By leveraging IoT integration, the ARPC system enables real-time monitoring of students' physical health parameters, such as heart rate and respiration rate, facilitating early detection of health issues and supporting overall well-being. The ARPC model, with its feature ranking and parallel data processing capabilities, achieves a high classification accuracy of 99.73%, outperforming conventional state-of-the-art techniques. This highlights the effectiveness of the ARPC system in accurately assessing students' performance in martial arts education. The results of the simulation analysis validate the efficacy of the ARPC model, demonstrating its potential as an automated classifier for continuous assessment in the elementary school martial arts education domain.

## REFERENCES

[1] Omata, K., & Imai, S. (2022). An exploratory study on PBL lessons using IoT teaching materials in elementary schools. Information and Technology in Education and Learning, 2(1), Trans-p009.

[2] Liao, Y. W., Hsieh, M. C., & Wei, C. W. (2021, July). Effectiveness of integrating AR and IoT technologies into environmental education for elementary school students. In 2021 International Conference on Advanced Learning Technologies (ICALT) (pp. 78-80). IEEE.

[3] Setiawan, M. I., Suwastika, N. A., & Prabowo, S. (2021). IoT-Based Kobela Teaching Aid for Mathematics Learning Multiplication and Division Materials for Grade II Elementary School Students. JURNAL MEDIA INFORMATIKA BUDIDARMA, 5(3), 1142-1149.

[4] Yulisetiani, S., & Hatta, P. (2021). Conceptual IoT Implementation in Post-Pandemic School Activities: A Case Study in Elementary Schools. IJIE (Indonesian Journal of Informatics Education), 5(2), 46-58.

[5] Jufriansah, A., & Khusnani, A. (2022). Thematic Learning Design Using the Internet of Things (IoT) at the Elementary School During the Covid-19 Pandemic. Jurnal Pendidikan Fisika, 10(1), 32-40.

[6] Permadi, H. S., Suwastika, N. A., & Al Makky, M. (2022). KPK and FPB Number Value Detection System using DAKOTA based on Internet of Things for Indonesian Fourth Grade Elementary School Students. JURNAL MEDIA INFORMATIKA BUDIDARMA, 6(2), 848-857.

[7] Tsuei, M., Chang, Y. C., & Chiu, J. I. (2022, June). Use of IoT Programming in Mudslide Disaster Prevention Education for Children. In HCI International 2022 Posters: 24th International Conference on Human-Computer Interaction, HCII 2022, Virtual Event, June 26–July 1, 2022, Proceedings, Part III (pp. 133-137). Cham: Springer International Publishing.

[8] Beng, J. T., Dewi, F. I., Amanto, A. F., Fiscarina, C., Chandra, D., Lusiana, F., ... & Tiatri, S. (2022, April). STEM Learning Model Design Using IoT for Primary School Students. In 3rd Tarumanagara International Conference on the Applications of Social Sciences and Humanities (TICASH 2021) (pp. 1117-1122). Atlantis Press.

[9] Xu, C. (2022). Research on the Use of Task-Based Language Teaching Method in English Language Teaching Based on Big Data 5G IoT Scenario. Journal of Sensors, 2022.

[10] Faryad, S., Batool, H., Asif, M., & Yasin, A. (2021). Impact of internet of things (IoT) as persuasive technology. IJ Information Technology and Computer Science, 6(2021), 16-28.

[11] Shikalgar, S. ., Yadav, R. K. ., & Mahalle, P. N. . (2023). An AI Federated System for Anomalies Detection in Videos using Convolution Neural Network Mechanism. International Journal of Intelligent Systems and Applications in Engineering, 11(1s), 218–227. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2496

[12] Ding, L., & Liang, Y. (2021). Cloud computing and internet of things in the evaluation of ecological environment quality in rural tourist areas in smart cities. Mobile Information Systems, 2021, 1-11.

[13] Mr. Rahul Sharma. (2015). Recognition of Anthracnose Injuries on Apple Surfaces using YOLOV 3-Dense. International Journal of New Practices in Management and Engineering, 4(02), 08 - 14. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/36

[14] Khan, A., & Ghosh, S. K. (2021). Student performance analysis and prediction in classroom learning: A review of educational data mining studies. Education and information technologies, 26, 205-240.

[15] Albulescu, I., Labar, A. V., Manea, A. D., & Stan, C. (2023). The Mediating Role of Anxiety between Parenting Styles and Academic Performance among Primary School Students in the Context of Sustainable Education. Sustainability, 15(2), 1539.

[16] Shaturaev, J. (2021). Indigent condition in education and low academic outcomes in public education system of Indonesia and Uzbekistan. Архив научных исследований, 1(1).

[17] Clark, A. E., Nong, H., Zhu, H., & Zhu, R. (2021). Compensating for academic loss: Online learning and student performance during the COVID-19 pandemic. China Economic Review, 68, 101629.

[18] El Said, G. R. (2021). How did the COVID-19 pandemic affect higher education learning experience? An empirical investigation of learners' academic performance at a university in a developing country. Advances in Human-Computer Interaction, 2021, 1-10.

[19] Ahammad, D. S. H. ., & Yathiraju, D. . (2021). Maternity Risk Prediction Using IOT Module with Wearable Sensor and Deep Learning Based Feature Extraction and Classification Technique. Research Journal of Computer Systems and Engineering, 2(1), 40:45. Retrieved from https://technicaljournals.org/RJCSE/index.php/journal/article/view/19

[20] Iglesias-Pradas, S., Hernández-García, Á., Chaparro-Peláez, J., & Prieto, J. L. (2021). Emergency remote teaching and students' academic performance in higher education during the COVID-19 pandemic: A case study. Computers in human behavior, 119, 106713.

[21] Iglesias-Pradas, S., Hernández-García, Á., Chaparro-Peláez, J., & Prieto, J. L. (2021). Emergency remote teaching and students' academic performance in higher education during the COVID-19 pandemic: A case study. Computers in human behavior, 119, 106713.

[22] Limniou, M., Varga-Atkins, T., Hands, C., & Elshamaa, M. (2021). Learning, student digital capabilities and academic performance over the COVID-19 pandemic. Education Sciences, 11(7), 361.

[23] Hammerstein, S., König, C., Dreisörner, T., & Frey, A. (2021). Effects of COVID-19-related school closures on student achievement-a systematic review. Frontiers in psychology, 12, 746289.

[24] Gopal, R., Singh, V., & Aggarwal, A. (2021). Impact of online classes on the satisfaction and performance of students during the pandemic period of COVID 19. Education and Information Technologies, 26(6), 6923-6947.

[25] Oducado, R. M., & Estoque, H. (2021). Online learning in nursing education during the COVID-19 pandemic: Stress, satisfaction, and academic performance. Journal of Nursing Practice, 4(2), 143-153.

[26] Martinez, M., Davies, C., Garcia, J., Castro, J., & Martinez, J. Machine Learning-Enabled Quality Control in Engineering Manufacturing. Kuwait Journal of Machine Learning, 1(2). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/122

[27] Alam, A. (2022). Positive psychology goes to school: conceptualizing students' happiness in 21st century schools while 'minding the mind!'are we there yet? evidence-backed, school-based positive psychology interventions. ECS Transactions, 107(1), 11199.

[28] Kart, A., & Kart, M. (2021). Academic and social effects of inclusion on students without disabilities: A review of the literature. Education Sciences, 11(1), 16.