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Original Article

An IoT-Enabled Machine Learning Framework for Automated Teacher Performance Feedback to Enhance Teaching Quality

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Abstract: Given the crucial role of teachers in the education system, robust mechanisms are necessary to enhance their teaching effectiveness. Through leveraging advanced technological methods, both teacher and student evaluation processes can be conducted with high accuracy. This study proposes an IoT-based automated teacher performance evaluation system that utilizes machine learning algorithms and computer vision techniques to provide immediate feedback on teaching performance to supervisors. The system analyzes key elements such as hand movements and the teacher's position in the classroom. By enhancing teaching performance, the model aims to improve student learning outcomes. In addition, to develop and test the system, a hypothetical dataset - called the teacher dataset - was created for this proposed model by collecting 35 publicly available videos from YouTube. This approach employs a ResNet50 pre-trained neural network for transfer learning and feature extraction to classify teacher behavior into 8 classes. Fuzzy logic converts the predictions into three teaching quality ratings (poor/medium/good). Using this custom dataset, the model achieved an accuracy of 84.8%, indicating strong performance. This approach enables automated feedback on teaching style, reducing the need for in-person evaluations by educational supervisors. The proposed system has the potential to significantly enhance the overall quality of teaching and learning.

1. Introduction

One of the most powerful and transformative aspects of the Internet and information technology is the Internet of Things (IoT) [1]. This innovation enables seamless communication between humans, devices, and the surrounding environment. IoT is a network-based system that collects data from indoor sensors and transmits it to embedded systems to generate appropriate responses. It has been widely adopted across various sectors, including traffic control, healthcare, energy management, and education [2].

In the context of education, the IoT represents a promising tool for enhancing the development of the education system. It can serve as a fundamental component of smart classrooms. When integrated with other intelligent learning tools, IoT contributes significantly to creating an interactive learning environment, enriching the learning experience, and supporting dynamic teaching practices [3].

As previously mentioned, to assess progress in any sector—including education—a creative and effective evaluation process is essential. This process aids decision-makers in identifying areas for improvement and making informed strategic decisions. Reliable evaluation results are necessary to identify weaknesses and implement corrective measures. If the evaluation method lacks accuracy, it becomes difficult to forecast future outcomes, and any attempt to improve the system may result in ineffective or superficial changes.

Modern pedagogical theories emphasize the importance of feedback in evaluating teaching methods and teacher performance. Continuous feedback allows educational managers to assess classroom performance and develop more effective strategies for future instruction. For teachers, receiving regular feedback serves as a valuable opportunity for professional growth, helping them refine their teaching style and better convey educational and scientific content to their students [4].

The body language of teachers is a critical component of the teaching process. It plays a significant role in fostering strong relationships between teachers and students, particularly in primary and secondary education. Establishing an effective educational connection is essential for successfully transmitting knowledge and ideas to all students [5]. One widely used teaching strategy is the grouping method, in which students are divided into pairs or small groups [6]. In such settings, the teacher's physical presence and movement within the classroom become key to maintaining effective communication with each group. The teacher's ability to move freely and monitor all groups contributes greatly to the overall quality of the instruction and student engagement.

The main goal of the feedback system proposed in this study is to evaluate the teaching process by identifying both strengths and areas for improvement. Particular emphasis is placed on analyzing body language and the teacher's positioning in the classroom, as these elements significantly affect instructional quality. While numerous studies have explored the use of smart technologies to provide feedback in education [7], most have focused primarily on assessing student comprehension and classroom behavior. It is concerning that insufficient attention has been devoted to evaluating teacher performance during instruction.

In response to this gap, this proposed system integrates the IoT with machine learning techniques to monitor teaching practices. It provides a comprehensive analysis of the teacher's body language and classroom positioning in real time. This system offers immediate, constructive, and automated feedback on teacher performance, making such insights readily available whenever needed. The proposed system extracts visual features from images of teachers and applies machine learning techniques to automatically detect hand movements and the teacher's position within the classroom. In the subsequent step, the captured images are transmitted to a central server via the network layer. The system then evaluates teacher performance based on predefined educational parameters that are manually configured on the server. Ultimately, the system classifies teachers into different performance levels, such as creative or non-creative, depending on their physical engagement and movement within the classroom. Teachers who demonstrate active physical presence and effectively use gestures and movement are classified as creative. In contrast, those who show limited physical involvement are categorized as having lower teaching performance [8].

The primary objective of this study is to classify teachers based on their hand movements and standing positions in the classroom using input data obtained from recorded classroom footage. Hand movements and the teacher's position within the classroom can be categorized into several distinct classes, with specific labels assigned to each possible state. Since the collected data will be used in both the training and testing phases of the model, the labeling and classification are initially carried out by domain experts.

Teacher performance is assessed using fuzzy logic rules, and the system generates immediate feedback reports, which are sent directly to educational supervisors. This eliminates the need for supervisors to attend classes regularly, and also reduces the instructional time lost to manual feedback collection methods, such as student questionnaires. In traditional evaluation systems, feedback is typically collected either through end-of-lesson student surveys or via in-class observation by administrators. Both methods are often complex, time-consuming, and do not reliably produce accurate or objective results. Consequently, they are not ideal for systematically evaluating teaching effectiveness. A more efficient and reliable solution involves leveraging modern technological tools. In this context, the IoT offers a practical and effective approach for improving the feedback process and enhancing the quality of teaching evaluations [9].

In order to achieve improved educational outcomes in the future, it is essential to adopt more effective and efficient feedback systems. Traditional methods of providing feedback require a lot of time and effort from teachers, students, and supervisors, making them unsuitable for implementing a continuous and reliable teaching evaluation process. A teacher performance evaluation system, such as the one proposed in this study, serves as a forward-looking tool aimed at enhancing student performance by improving instructional quality. Given that the learning outcomes of students are directly influenced by the effectiveness of teaching, it is critical to invest in and improve systems that provide meaningful feedback on teaching methods [10]. Such an approach can foster a more dynamic and effective classroom environment, underpinned by enhanced instructional practices.

The structure of the paper is as follows: section 2 presents a literature review summarizing recent studies relevant to the proposed model. section 3 describes the methodology, including the creation of datasets, the preprocessing mechanisms employed to enhance data quality, and an explanation of the structure and operational principles of the basic model. Section 4 reports the results, with particular emphasis on the application of fuzzy logic in evaluating teacher performance based on the system's output.

2. Related Works

In recent years, the entry of various technologies into human life and in all areas has expanded significantly. Education, as the most important part of society, has contributed a lot to this. Currently, the use of technological systems has been prioritized to develop and improve the performance of all parts of the educational system both in teaching and school management.

Nejeru *et al.* [11] investigated how the IoT can be employed to collect and analyze data, with the aim of generating actionable knowledge to promote online learning in higher education institutions. In their study, various data mining algorithms were applied to organize, integrate, sort, and analyze the data, ultimately producing reports tailored for different management departments.

Narayanan *et al.* [12] have invented an IoT system that bridges the gap between a traditional classroom and an online learning environment. The proposed method pays attention to three states of students: wakefulness, sleepiness and invisibility in class. In this study, the authors have proposed a simple geometric model to identify the corners of students' eyes. However, this proposed approach strengthens the evaluation of the e-learning process by warning students when they become distracted during an e-learning session.

Matsuo *et al.* [13] presented an experimental platform for e-learning based on the IoT, using Raspberry Pi installed on Raspbian. They have done gamma brain wave studies with a student from their lab. They used mind wave mobile to acquire data and examined four states: sleep, rest, movement and being active. Then, they have clustered the data using mean change clustering algorithm. The evaluation results show that their testing platform can analyze the human condition by using delta, gamma, alpha and theta brain waves.

Tan *et al.* [14] suggested an IoT-based system that uses sensors to analyze occupancy, temperature, and humidity in the classroom. This method utilizes moving average computation and correlation analysis to smooth data and detect correlations among environmental variables. In order to enhance learning environments and minimizing energy consumption in educational environments, the model offers real-time data visualization and remote control of appliances using a mobile application.

Zhao *et al.* [15] used a multimodal neural network called ProsodyBERT with the aim to provide a workable method for recognizing the teacher's speech emotions in smart classrooms. It processes text and prosodic characteristics by combining one dimensional convolutional neural network, Gate Recurrent Unit, and BERT neural network. The method achieves 82.1% accuracy on a bespoke teacher emotion multimodal teacher emotion dataset, outperforming other methods.

Saxena *et al.* [16] proposed a model to classify students into three types of learning styles based on visual, auditory and Kinesthetic theory using the IoT. Further, Satu *et al.* [17] proposed a platform named Intelligent of Learning Things as an educational platform. It is an IoT for blended learning, where innovative learning methods and strategies are used to improve the traditional learning process. This platform also incorporates the concepts of computational data mining, artificial intelligence and sensor networks.

Shaurya *et al.* [18] have explained that many students encounter difficulties adapting to traditional teaching methods. For example, slow learning speed and not going to school due to family issues. This article deals with previous educational research in which the IoT has been used to help solve the mentioned problems. Also, in this research, an educational model based on IoT is proposed to improve learning and educational environment. On the other hand, Khaleel and Yussof [19] investigated the possibility of using the IoT approach to monitor students' attendance and presence in the school campus in real time, in order to ensure their safety. In addition, Hu [20] proposed a pedagogical assessment system utilizing machine learning methods. By evaluating the performance of several classification algorithms, their model demonstrates that the weighted naive Bayes (WNB) algorithm has the highest accuracy of 81.7% compared to the traditional naive Bayes (75.1%) and back propagation (68%) algorithms. Dehbozorgi [21] developed a model to assess students' conversation and their stated emotions as they work on class tasks in groups and explore if their conversations are course-related or not by applying topic extraction to the conversations. However, nonnegative matrix factorization model, a well-liked unsupervised learning method, was applied in order to enhance the topic extraction procedure.

Guan *et al.* [22] suggested the real-time processing of the video recorded from the classroom through a software system and face recognition technology, in order to provide an important basis for evaluating the quality of teaching. The researchers highlighted key points. First, the evaluation of the teaching system must include feedback that can be significantly improved through teaching to help students grow. Second, the evaluation must be highly effective and accurate. Finally, the system must take into account future modifications. Huang *et al*. [23] developed a teaching quality assessment system based on Support Vector Machine (SVM) technology to address the limitations of traditional subjective evaluation methods. The authors identified that conventional teaching quality assessment approaches suffer from subjectivity, computational complexity, and weak effectiveness, making it difficult to obtain objective and accurate evaluations.

Ali [24] have created programs for IoT devices with voice capabilities that can communicate with students and teachers in the context of textbooks. Their proposed technique uses artificial intelligence to recognize user expressions and machine learning to learn new expressions. In addition, the authors have developed applications for a speech-capable IoT device that takes the human voice as an input data set. Ciolacu *et al.* [25] introduced a new method to promote artificial intelligence in Education 4.0, the main activity of researchers is about an artificial intelligence-assisted education process that includes smart sensors and wearable devices for self-directed learning. The aim of the authors is to estimate the final grades of the students before participating in the final exams. Verma *et al.* [26] invented a design-driven approach to develop a tool to generate reports on engaging educational videos using convolutional neural network and deep learning by classifying teachers' images as an AI methodology aiming to create an AI-enabled tool. The authors used the traits and metrics of interesting teaching videos that were published in different research. This tool can be used to identify engagement-enhancing teachers' behaviors and motions in recorded lecture films, as well as create a report on engaging teaching videos. However, deep learning model is used for video analysis classification task. By using the oversampling approach, the model was further enhanced and produced promising results with average accuracy. Finally, the study reached appropriate conclusions, for example recall, f1-score, and balanced accuracy of 68, 75, 73, and 79%, respectively, in classifying the annotated videos at the indicator level.

Zahra [27] tried to solve the problem of interaction between teachers and students in electronic education systems by actively executing queries and developing a new method for designing decision support systems. Based on the data available in the data management system, the system allows teachers to answer questions that identify students' academic performance using data mining methods.

3. Materials and Methods

In this section, an appropriate implementation method will be proposed to assess teacher performance based on the data collected during the teaching process. Machine learning and deep learning techniques have demonstrated significant success and effectiveness in object recognition and feature extraction from images and video clips.

Neural networks were employed in this study as advanced computational models capable of performing image processing tasks with high precision and reliability. Given their strong performance in visual pattern recognition, they were identified as the most suitable approach for classifying teachers' hand and body movements in the classroom.

An initial phase of methodological evaluation was conducted to determine the optimal configuration for this application. Considering the nature of the dataset, the variability of classroom environments, and the objectives of accurate movement classification, a pre-trained neural network integrated with feature extraction techniques was selected as the core analytical method. This configuration ensures both computational efficiency and robust performance in recognizing motion-related features.

The overall system architecture consists of three layers: (1) the IoT sensor layer, (2) the communication layer, and (3) the processing layer. In the sensor layer, video data are acquired using strategically positioned cameras that capture the teacher's full-body movements from multiple angles. The recorded data are then transmitted through the communication layer to the processing layer via secure network protocols. Within the processing layer, the captured frames are pre-processed, relevant features are extracted, and the data are classified using the pre-trained neural network model hosted on a dedicated server

Next, the features of the teacher's images are extracted and analyzed on the server. Subsequently, machine learning techniques are applied to evaluate the teacher's body movements and position within the classroom to determine whether the teaching style exhibits creativity. Finally, an automated feedback report is generated and sent to the supervisor via the application layer. The overall architecture of the model is illustrated in figure. 1.

Currently, the Python programming language is one of the most popular choices among developers and is widely used in machine learning and neural network projects. Therefore, it was selected as the implementation language for the proposed model in this research.

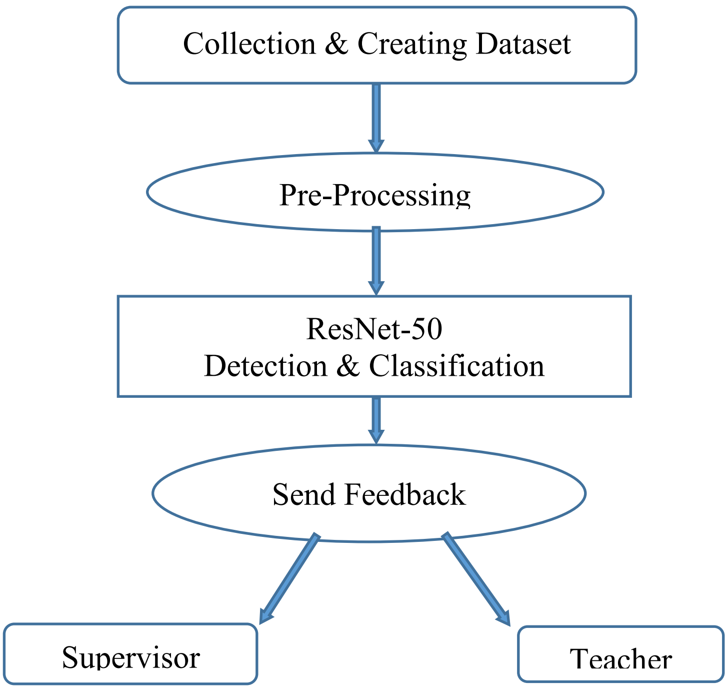


Figure 1: The general process of the proposed method.

3.1. Image Recording

After the classroom images are recorded by the installed cameras, they are provided as basic input data to the next layer of the IoT system. The network or communication layer functions as a real-time data transmitter to the computing layer.

3.2. Transmit Images

Since educational centers and organizations are generally limited to a specific area or building, they do not face many of the challenges commonly encountered in IoT systems used in other fields. By selecting a simpler communication technology—such as Zigbee—the desired IoT system can be implemented effectively. The data collected from the perception layer (i.e., the cameras installed in the classroom) are transmitted to the school's central server layer using the Zigbee communication protocol [28]. At this stage, computations are performed according to the objectives defined in this research, and the evaluation results are delivered to the end users.

3.3. Convert Images

To prepare the dataset for processing in the programming environment, the Python programming language is used to convert each teacher's video clip into 240 individual frames—one frame per second. In total, the 35 video clips used in this study are converted into 8,457 distinct images. However, the resulting images vary in size and resolution, which leads to an imbalance in the dataset.

3.4. Teacher Dataset

The dataset used in this research is derived from recorded classroom images. These images are required to gather visual information about the teacher's hand movements and standing position. To ensure full coverage of the classroom space and clear visibility of the teacher's body during instruction, video cameras should be installed in the corners of the classroom.

Despite extensive efforts to find a suitable dataset, no existing dataset was found that aligned with the main objectives of this study. As an alternative, publicly available classroom video clips from the website YouTube.com were used to construct a custom hypothetical dataset. A total of 35 clips, each 240 seconds in length, were collected from 35 different teachers and classrooms. Of these, 33 videos were used for training and testing, while the remaining 2 were reserved for teacher validation and were not included in the main model.

The videos were sourced from elementary school classrooms, consistent with the study's primary aim of evaluating elementary school teachers. Table 1 shows teacher dataset details.

It is important to note that the course content was not considered when selecting the videos. The classrooms represent diverse regions, countries, and languages. The videos are similar in terms of framing, content, and camera angles. This uniformity contributes to a more consistent data set and facilitates the processing tasks.

Table 1: Teacher dataset details.

Number of classes	Total number of frames	Frames per teacher	The length of each clip	Number of teachers
8	8456	240	4 minutes	35

3.5. Image Labeling

The information extracted from the images is recorded in a CSV file. Based on scientific criteria related to teaching methods, the features in the hypothetical dataset are defined according to the teacher's hand movements and standing position within the classroom. For each teacher in each image, the corresponding features are assigned appropriate values. A sample of the teacher dataset is shown in table 2.

Table 2: A scaled-down example of the teacher dataset CSV file.

Teacher_ID	Image_ID	Hand_Movement	Classroom_Zone	Situation	Act_Class
1	Frame0	1	1	Up,mid	1
1	Frame1	1	1	Up,mid	1
1	Frame2	1	1	Up,mid	1
1	Frame3	1	1	Up,mid	1
1	Frame4	1	1	Up,mid	1
1	Frame5	1	1	Up,mid	1
1	Frame6	0	1	Down,mid	5
1	Frame7	0	1	Down,mid	5
1	Frame8	0	3	Down,left	7
1	Frame9	0	3	Down,left	7
1	Frame10	2	3	Up,left	3
1	Frame11	2	3	Up,left	3

Each teacher is represented by approximately 240 frames, resulting in a total of 8,457 frames, sequentially labeled from frame0 to frame8456. Since all images must be included in a single dataset, the frame numbers are organized in ascending order. For instance, the images for the second teacher begin at frame241 rather than frame0. This pattern continues for subsequent teachers, with each teacher's frames following the previous teacher's in sequence, up to the final image in the dataset, frame8456.

3.6. Teacher Dataset Details

As shown in figure 2, an identifier labeled (Teacher_ID) is assigned to each teacher, ranging from 1 to 35. Each image extracted from the video—converted into individual frames—is associated with a unique (Image_ID). The feature (Hand_movement) represents whether the teacher's hand is in motion within a given frame. This feature has two possible values: a value of 1 indicates hand movement, while a value of 0 denotes that the hands are stationary. In the stationary state, the teacher's hands are typically positioned alongside the body, facing downward. The classroom zone feature indicates the teacher's spatial position within the classroom in each frame. For analysis purposes, the classroom is divided into four zones:

- (mid): The central area of the classroom, in front of the board, considered the teacher's default position
- (right): The right-hand side of the classroom, from the perspective of the camera and students
- (left): The left-hand side of the classroom, also from the perspective of the camera and students
- (front): The area among the students or near student groups; this zone is considered particularly significant, as the teacher's presence in this space often contributes meaningfully to effective teaching

The features of hand movement and classroom position should be jointly evaluated by educational experts, as their combined interpretation is critical to understanding teaching behavior. Accordingly, in the dataset, both features are paired to represent all possible combinations of hand movement and teacher position.

3.7. Hand Movements and the Position of theTeacher

The feature (situation) represents all possible combinations of the teacher's behavior in the classroom, derived from the integration of hand movement and teacher position in the classroom. This feature is used to categorize the teacher's activity status and forms the basis for classifying various teaching scenarios. The full set of hand movement and classroom position combinations is illustrated in table 3. The (Act_Class) feature serves as the final classification label for the teacher's situation in the classroom and is determined based on the (situation) feature. By combining the two binary components—hand movement (moving or still) and classroom zone (mid, left, right, front)—a total of eight distinct classes is formed. These classes represent the comprehensive labeling scheme used for the dataset.

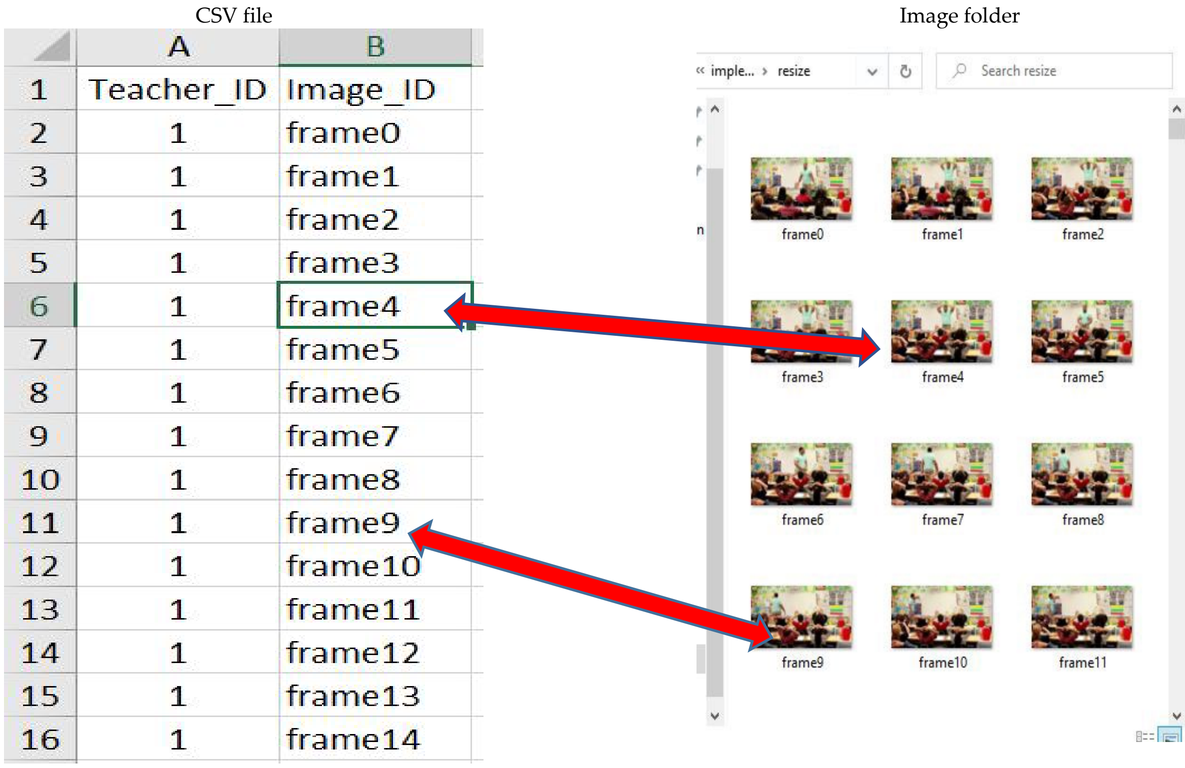
Table 3: Combined modes of hand movement and position.

Possible situations	Hand movement/position	Category (label)
Up, mid	Having hand movement / front - middle of the class	0
Up, right	Having a hand movement / right side of the class	1
Up, left	Having a hand movement / left side of the class	2
Up, front	Having hand movement / close to students	3
Down, mid	No hand movement / front - middle of the class	4
Down, right	No hand movement / right side of the class	5
Down, left	No hand movement / left side of the class	6
Down, front	No hand movement / among students	7

3.8. Data Preprocessing

The dataset used in this research comprises classroom videos recorded live and subsequently transmitted to the school's server via the IoT transmission layer. As explained in previous sections, due to the unavailability of an appropriate existing dataset, a custom dataset was manually constructed to align with the core objectives of this study. As the primary data consisted of classroom images collected under controlled conditions, potential issues such as noise, missing values, and inconsistent labeling were effectively minimized. Significant effort was made to ensure the highest possible image quality, thereby enabling the model to achieve optimal performance.

In addition, the data set consists of a CSV file with a folder of recorded images from the class, the CSV file was created manually based on both the characteristics of the teacher's hand movement and the standing position in the images. Finally, the attribute (Act Class) is inserted as a label or class to which the image belongs. In the first step, each image should be read in the programming environment, afterwards the images will be linked to the CSV file. Therefore, based on the attribute (Image_ID), all the images are loaded in the program, that each image belongs to its own name in the attribute (Image_ID). Figure. 2 displays the link between the images and the CSV file.



	A	B
1	Teacher_ID	Image_ID
2	1	frame0
3	1	frame1
4	1	frame2
5	1	frame3
6	1	frame4
7	1	frame5
8	1	frame6
9	1	frame7
10	1	frame8
11	1	frame9
12	1	frame10
13	1	frame11
14	1	frame12
15	1	frame13
16	1	frame14

Figure 2: CSV file association with individual images.

3.9. Data Splitting toTrain and Test Set

In machine learning and usually in the implementation of classification algorithms, the primary data must be divided into three groups, that is, the data splitting process must be implemented. Splitting of data into training data and test data (Train-Test Split) is a method to measure the performance quality of a machine learning algorithm. In the other hand, data splitting can be used in classification or regression problems and generally this approach is used in any type of supervised learning algorithms. The algorithm learns from the training data and the performance of the built model is determined through the test data [29].

In dividing the primary data, the value of each part should be determined. For better learning of the model, usually more training data is considered than test data. In most of the implementation work, training data set to be 80% and test data is 20% of total data. Due to the imbalance of the images of the teacher data set, the data of this project are divided into 90% for training and 10% for testing, so that the learning process on the images can be carried out well and the classification work can be performed with optimal accuracy.

3.10. Data Normalization

Normalization is a suitable method for data smoothing and is performed as an important step of data preprocessing. Especially in the presence of image data, which are essentially a very complex and different data set, normalization is used as a very important and necessary operation. On the other hand, normalizing and placing the data in a limited range makes the structurally large data not justify the results.

The pre-trained model called residual networks (ResNet50), which will be explained in the next section, has a special command to normalize the data before executing the neural network layers that make up the model and places the images in the range between (1, -1). This means, other data do not need normal normalization methods, because the trained model itself has a strong and suitable method for data normalization and scaling, which normalizes the data in the best way.

3.11. Basic Model

Through extensive review and analysis in the field of human and object recognition in images—core components of image processing— neural networks were identified as highly effective models for this type of task. Neural networks are particularly well-suited for detecting complex and diverse features within images, and they demonstrate strong performance in classification tasks with high accuracy. Given their proven capabilities in image processing applications, neural networks were selected as the foundational model for this research [30].

In the previous sections, the data collection process within the IoT platform was described. Data acquisition occurs at the lowest layer of the system, primarily through cameras installed in classrooms. This setup enables real-time feedback on teachers' instructional performance. To obtain this feedback effectively, the recorded classroom images must undergo detailed computational analysis. To facilitate real-time data transmission, an intermediate layer—referred to as the communication technology layer—is required between the first layer (data collection) and the third layer (processing layer). This layer is responsible for transmitting data from the collection layer to the computation layer, where the proposed main model is executed. In this study, Zigbee technology is employed as the communication layer. Zigbee is an appropriate choice for the proposed model due to its advantages in geographical coverage, low latency, and energy efficiency.

Once the data reaches the third layer—typically a local computing unit such as a computer at an educational center or school—computational operations are performed on the raw data. To obtain a comprehensive and interpretable understanding of teachers' performance, the output must be meaningful to domain experts. This function is handled by the third layer, where the core model for data processing is implemented. Before applying the main model, the data must be transformed into a suitable format to ensure optimal model performance. This includes image classification with high accuracy. Preprocessing tasks at this stage may involve video-to-image conversion, normalization, and resizing of images.

The next stage is the implementation of the main classification model. In this research, one of the pre-trained neural networks has been used, which has a very strong performance and high accuracy in image classification. ResNet50 pre-trained model, after freezing the upper layer or the classifier layer and adding a few layers for the classification of the teacher's data set, performs the task of classifying classroom images into eight predefined categories in the best possible way, finally on According to the evaluation results of teachers' hand movements and positions, it is possible to provide real-time feedback on the level of their teaching methods.

Considering the task of image classification and the overarching research objectives being pursued, the implementation of such projects should be resumed with optimal accuracy. It was not possible with any simple model or classifier, because the task required identifying a highly capable model to ensure accurate classification of the substantial image dataset. Of course, after trying different models, the pre-trained Resnet50 type network gave the best result and achieved the goals of this research to a large extent; Therefore, it was chosen as the main model in this research.

3.12. ResNet Model

Residual network (ResNet) for short, is an artificial neural network that helps to create a deeper neural network by using skip connections to jump over some layers [31]. In the structure of the ResNet model, it's obvious how the jumping technique helps to create deeper layers of the network without dealing with the gradient vanishing problem.

ResNet was introduced for the first time in 2016 [32]. Among other masterpieces, the authors were able to win first place in the Image Net Large-Scale Visual Recognition Challenge in 2015. ResNet had the deepest architecture until that year and after that it is still one of the deepest. Although ResNet exhibits a substantially greater depth compared to the Visual Geometry Group (VGG) family of networks, the actual weight size of the model is smaller due to the use of average pooling instead of a fully connected layer. The ResNet model offers several merits. It increases the speed of training and achieves notably high classification accuracy. Moreover, it is designed to learn the differences between extracted features; if a learned feature is determined to be unhelpful for the final decision, the model adjusts the weight of that feature to zero.

ResNet is originally trained on the ImageNet dataset, and using the transfer learning method, it is possible to load pre-trained convolutional weights and train a new classifier on top of it. In the implementation of the ResNet pre-trained model as transfer learning, the upper layers are not considered, the network is trained on new data, and the classification of new data is done. That is, only the convolutional weights that are trained on ImageNet data are loaded. After loading the model, the layers of the base model are set as "untrainable", in other words, they are frozen and will not be trained again, this will surely shorten the execution time of the main model. ResNet has different versions including (ResNet-18, ResNet-34, ResNet-50) and so on. Numbers represent the number of layers of each type, although the architectures are similar.

Despite the greater complexity of the ResNet model compared to similar models such as VGG19. Although the number of parameters in ResNet seems to be much more and the model has more parameters! But it has better performance. The reason behind the good performance of the model is many layers that gradually learn more complex features. First layer the edges, second layer the shapes, third layer the objects, fourth layer the eyes, and so on [33].

3.13. ResNet Architecture

There is a simple network with 34 layers in the ResNet architecture, inspired by VGG-19, in which intermediate connection or skip connections are added. skip connections or residual blocks transform the architecture into a residual network as shown in the figure. 3.

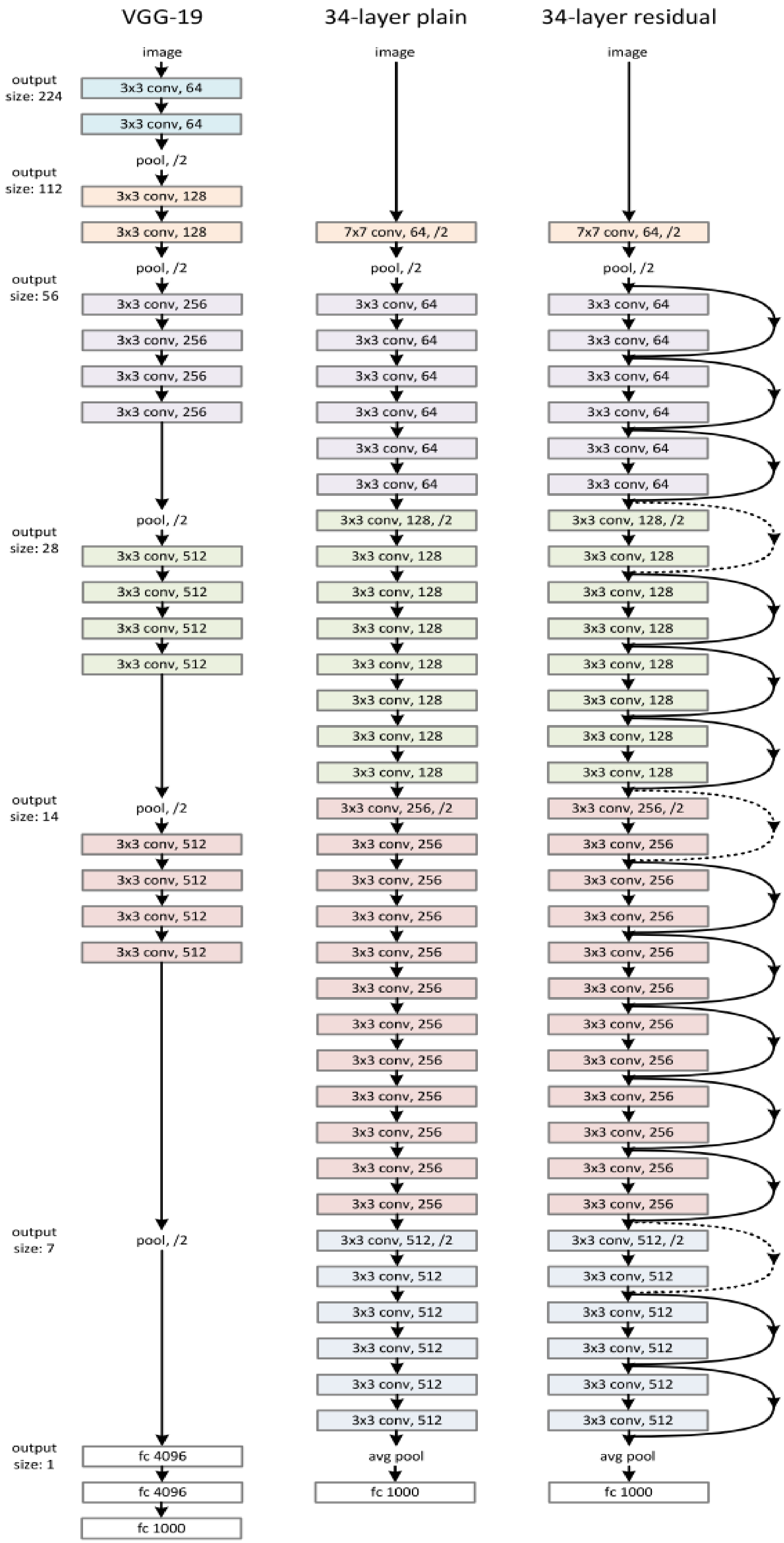


Figure 3: The architecture of ResNet [32].

3.14. ResNet50

Mainly, to solve a complex problem, some additional layers are placed in deep neural networks, which leads to improved accuracy and performance. The intuition behind adding more layers is that these layers gradually learn more complex features. For example, in the case of image recognition, the first layer may learn to recognize edges, the second layer may learn to recognize textures, and similarly, the third layer may learn to recognize objects and so on.

Deep residual network architecture was developed to overcome the problems in deep learning training, because deep learning training, in general, takes a lot of time and is limited to a certain number of layers. The advantage of ResNets model compared to other models is that despite the deepening of the architecture, its accuracy does not decrease. In addition, the computational work is lighter and the ability to train networks is better [34]. The ResNet pre-trained neural network has different types, all of which, despite the number of different layers, are implemented based on the same concept. Resnet50 type can work with 50 layers of neural network. In Keras Applications, there are deep learning models that provide pre-trained weights. These models can be used for the purpose of prediction, feature extraction and Fine-tuning [35].

3.15. Fuzzy Logic

Fuzzy logic refers to a form of reasoning designed to handle imprecision and ambiguity. In everyday life, situations often arise in which it is difficult to determine whether a decision is entirely right or wrong. In such cases, fuzzy logic offers a flexible and valuable framework for modeling uncertainty. It enables the quantification of uncertainty in any given situation, which is why it is sometimes referred to as 'doubtful logic,' as its conclusions inherently incorporate degrees of doubt.

Fuzzy logic is based on human decisions, so it can be considered development (Aristotle Logic) or Boolean Logic. At the same time, fuzzy logic is a kind of approach in computer science, which is an alternative to the common method of true or false (zero or one) Boolean logic, on which modern computers are designed. In most parts, states 0 and 1 are usually considered as extreme states of truth, but several true states are also placed between these two states [36].

Fuzzy logic closely mirrors the approximate reasoning processes of the human brain. In fuzzy logic, membership degree is considered instead of absolute membership. Considering the properties of fuzzy logic and how it works, can be used as a suitable metric to evaluate the level of teaching method based on the prediction of teachers' images.

4. Results

The reason behind the good performance of the ResNet model can be that despite having many layers, more complex features are able to be gradually recognized. Deep residual networks (ResNets) can speed up the training process and achieve more accuracy compared to their equivalent neural networks. The advantage of the ResNets model compared to other architectural models is that the accuracy of this model does not decrease, despite the deepening of the architecture. In addition, at the same time, the ability to train the network is better and its computational work becomes lighter. Adding suitable new layers to classify the existing images in a way that forms a suitable combination with the pre-trained network has a significant effect on the overall performance of the model and the accuracy of the classification task. Keeping in mind the mentioned details, the accuracy of the teachers' image classification regarding the eight desired classes in this research was close to 84.8%, which is a good level of accuracy in comparison with other models in similar research. Table 4 shows accurate metric values.

Table 4: Performance metric evaluation.

Metrics	Accuracy	Precision	Recall	F1 score
Value	84.8%	84.9%	84.8%	84.7%

Accuracy is one of the evaluation metric of classification models. In fact, it is the most important and common of them. Accuracy is the fraction of predictions that the model has made correctly.

Accuracy = number of correct predictions / total number of predictions

Considering the details of the teacher's data set and the goals that were pursued in this research, the cost of False Positive and False Negative in the research are almost equal. Therefore, the focus here is on the value of accuracy (Precision): It is a percentage value that shows the accuracy of positive predictions.

(Recall): It is a percentage value that shows how many positive cases have been correctly predicted.

(F1 score): F1 score is a weighted harmonic mean of (Precision) and (Recall).

F1 Score = 2 * (Recall * Precision) / (Recall + Precision).

The prediction result of the images is not a binary answer (yes or no) and the teacher's performance is determined based on all those 240 images. It is possible that each image belongs to one of the eight defined classes.

To evaluate the performance of the first teacher, the total number of instances for each class across all 240 predicted classes was counted, and the corresponding percentage was calculated relative to the total predicted instances. Using fuzzy logic three distinct thresholds were established for each performance level—poor quality, middle quality, and good quality. Based on the thresholds outlined in table 5, the level of each class was ranked accordingly. The final teacher quality was then determined by aggregating the results from all eight available classes; the performance level occurring most frequently among these classes was assigned as the teacher's overall quality.

Table 5: Threshold of the quality of classes.

Thresholds	Quality of Classes
Less than 5%	Poor
5-10%	Middle
More than 10%	Good

To explain more, for example, in the evaluation of a teacher, 15% of the predictions are in the first class, as a result, the teacher receives a (good) rating in that class, and so on.

Finally, the results of all eight classes were analyzed and compared, each of the qualities was higher, that will be the final result. If for a teacher, the results of 3 classes are poor, 4 classes are middle, and 1 class is good. Then the final result of the teacher's teaching quality is middle.

4.1. New Sample - Results Analysis

Images of the 34th and 35th teachers were used as new samples for prediction and evaluation with the constructed model. The images of these teachers are the same as the previous pictures that were used in the implementation model and learning section. They are clips of 240 seconds, each of them will be converted to 240 frames later. Based on the results of predictions, the teachers will be ranked using fuzzy logic to rate and grade them. At the same time, Fuzzy rule construction and ranking specification are based on the experience and opinions of experts in the field of education.

Data pre-processing and preparation is done on both teachers excluding for validation. Afterward, using the built model, classes of 240 images of each teacher will be predicted individually based on predictions and using the law of fuzzy logic, the final evaluation of each teacher is done.

Because every 240-second video has been converted into 240 images, so each image is equivalent to one second; The duration of each image class can be determined based on its frequency in the predictions. Table 6 presents the classification results for the thirty-fourth teacher.

Table 6: Results of the thirty-fourth teacher classes.

Evaluated teacher	Class zero	Class one	Class two	Class three	Class four	Class five	Class six	Class seven
34th	42%	4%	36%	1%	6%	2%	0.4%	7%

As shown in table 7, based on hand movement and standing position during the lesson the result of evaluating the teaching method of the thirty-fourth teacher is poor level.

Table 7: The final result of the thirty-fourth teacher.

Class quality	Quantity
Poor	4
Middle	2
Good	2
Overall result	Poor

The prediction results for the 34th example, as shown in figure 4, allow examination of the frame classes individually, providing a broader understanding of the model's performance.

```
[0 2 0 0 0 0 3 2 1 0 0 0 0 0 4 2 0 0 7 7 0 0 0 0 7 0 7 0 4 0 0 0 1 0 0 0 0
 0 0 1 4 0 0 2 0 0 0 2 2 1 0 7 2 2 2 2 2 2 0 0 5 0 0 0 4 1 0 1 0 0 0 0 0 7
 7 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 2 0 0 0 0 0 2 2 2 0 2 2 2 2 2 2 2 2
 2 2 0 2 2 2 2 0 2 4 7 7 2 0 2 2 2 2 0 0 2 2 0 2 2 2 0 3 0 2 2 2 2 2 1 0 0
 0 2 2 2 2 4 7 7 4 0 7 0 0 4 4 6 0 4 0 0 0 4 4 0 7 5 5 1 0 5 5 7 7 2 2 2 2
 2 0 4 1 1 7 7 4 0 4 0 0 0 0 0 0 2 0 0 0 0 0 0 2 2 0 0 0 0 2 0 0 0 0 0 2 0
 0 0 0 0 0 2 2 2 2 2 2 2 2 2 0 2 2]
5
[101, 10, 87, 3, 15, 5, 1, 17]
up,mid 101 seconds
up,right 10 seconds
up,left 87 seconds
up,front 3 seconds
down,mid 15 seconds
down,right 5 seconds
down,left 1 seconds
down,front 17 seconds
```

Figure 4: The prediction result of the 34th teacher's classes.

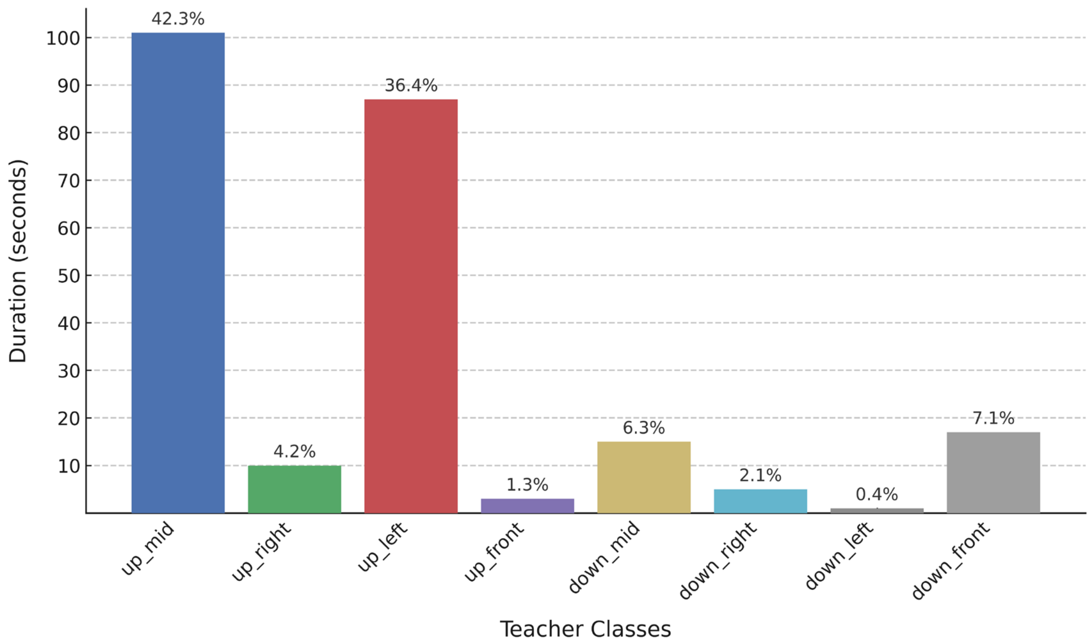


Figure 5: The result of the thirty-fourth teacher's classes.

The results for each mentioned class for 34 teachers are shown in figure 5. The final result of the teacher is shown in the graph as shown in figure. 6, which are all three levels: good, middle and poor.

Finally, in order to enhance strengths and eliminate weaknesses, the educational supervisor should give the necessary recommendations to the teacher based on the evaluation results.

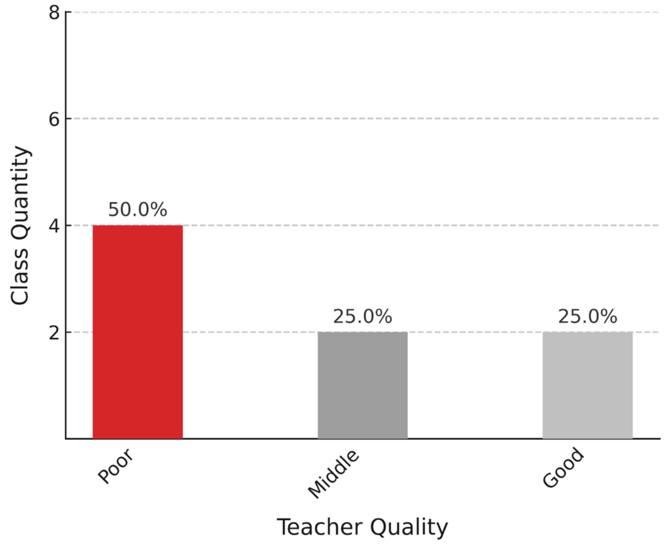


Figure 6: The final evaluation chart of the thirty-fourth teacher.

5. Discussion

After building the main model by removing the last layer of the pre-trained model, suitable layers were added with the classification of the new case. The built model showed that with the least complexity and a very favorable procedure, it performs the classification operation of the teacher data set according to the pre-determined number of classes [37]. In comparison with other models or works similar to the problem in this research, the performance quality explanatory diagrams show that the model built for the implementation work had satisfactory performance [38]. As a result, the classification of images has been very favorable. The high quality of the classification work subsequently leads to the accurate evaluation of the teacher's teaching method and the preparation of reliable real-time feedback. Although the data set used in this research is relatively unbalanced and complex, the precise selection of the main classification model was done with very good accuracy. Regardless of the fact that the residual network ResNet is a complex neural network with many layers, the use of skip connections solves the shortcomings of the network to a large extent [39]. Considering the complexity of the classes and imbalance of the data set, as a result of utilizing useful techniques related to the proposed model, the implementation operation was carried out with high accuracy (84.8%). This amount of accuracy is considered an acceptable performance for the proposed model [40].

5.1. Performance of the Model Compared to a Similar Model

In the implementation process of this research, our goal was to build a model whose accuracy and quality of performance is better than previous similar works that were used as preliminary studies in conducting this study. In 2018, James *et al.* [38] proposed an innovative system for evaluating the classroom environment based on behavioral signs and speech features using machine learning algorithms. Researchers have developed the system called CLASS with the aim of tracking and coding teacher-student interactions in order to provide reliable feedback on the teaching process.

The process of extracting the features of students' and teachers' conversations after recording the speaker is a part of speech analysis. In the same way, in video analysis, emotional features are extracted inform the faces of students and teachers. The dataset used in the CLASS system is classroom videos recorded from 250 preschool schools, and the time of each class was approximately 20 minutes.

Researchers have used various machine learning algorithms to evaluate the space and positive atmosphere of the classroom. At the same time, they have used the audio and images recorded separately and compositely as primary data and in order to examine the details of the model quality.

As illustrated in table 8, researchers have found that the combination of video and audio leads to an increase in the quality of system performance. The results of this research emphasize the possibility of predicting classroom situation using facial expressions and low-level voice features. Furthermore, video features can increase the understanding of the mood of the class.

Table 8: Performance accuracy of CLASS system algorithms [38].

Classifiers	Audio Features only			Video features only			Audio and video features combined		
	Weighted average of Precision	Weighted average of Recall	Weighted average of F_1-score	Weighted average of Precision	Weighted average of Recall	Weighted average of F_1-score	Weighted average of Precision	Weighted average of Recall	Weighted average of F_1-score
Random-Forest	0.73	0.77	0.75	0.71	0.80	0.74	0.76	0.80	0.77
Gradient Boosting	0.75	0.78	0.76	0.74	0.80	0.75	0.75	0.80	0.77
Decision Tree	0.72	0.72	0.72	0.72	0.74	0.73	0.73	0.77	0.75
SVM-Linear Kernel	0.74	0.62	0.66	0.75	0.73	0.74	0.76	0.67	0.70
SVM-Gaussian Kernel	0.73	0.63	0.67	0.73	0.77	0.75	0.74	0.69	0.71
AdaBoost	0.68	0.76	0.71	0.69	0.76	0.72	0.77	0.81	0.78
KNN	0.73	0.74	0.73	0.71	0.80	0.74	0.75	0.75	0.75
Logistic Regression	0.76	0.63	0.67	0.77	0.68	0.71	0.76	0.67	0.70
Gaussian Naive Bayes	0.76	0.75	0.75	0.73	0.54	0.58	0.75	0.78	0.76

Despite the dataset utilized in the proposed system being relatively unbalanced and exhibiting greater complexity than that of the CLASS system, the proposed model demonstrated a marked improvement in classification accuracy.

The integration of technological advancements into the field of education has become an increasingly prominent subject of scholarly discussion and debate. Technology companies and professionals have developed a range of learning tools aimed at enhancing the quality of educational systems. Teachers—often regarded as the cornerstone of educational success or failure—must be prioritized in any initiative that seeks to advance the field of education.

Providing continuous, real-time feedback on the teachers' performance represents a significant step forward as it enables the identification and correction of weaknesses in the used instructional methods. The successful implementation of the proposed method in this study aligns with the research objectives. The findings demonstrate that leveraging the IoT framework and machine learning algorithms can enable an efficient and accurate real-time feedback system for evaluating teacher performance, with minimal human effort and time investment.

Future research could extend the model's capabilities by incorporating additional influential elements in the teaching process and regarding the quality of student learning outcomes, such as analyzing the teacher and students' vocal attributes and facial expressions. Replacing the current pre-trained neural network with alternative architectures or employing more advanced algorithms for feature extraction and human recognition could improve image classification accuracy. Hardware improvements, including optimizing the quality and installation angles of video cameras, would facilitate the creation of richer and more suitable datasets.

One limitation of the current model is its inability to assess teachers with complete physical disabilities, such as the loss of limbs. Addressing this gap could involve developing an adapted version of the model or designing a dedicated framework for evaluating teachers with disabilities. Collectively, these enhancements would expand the scope, precision, and inclusivity of the proposed system, making it an even more valuable tool for educational quality assessment.

6. Conclusions

In the proposed model, a novel method is introduced to evaluate teachers' instructional styles and to provide real-time feedback on their performance within the framework of the IoT using machine learning techniques. The data used in this study consists of recorded classroom images captured via video cameras. These images are transmitted to the school's server computer through the Zigbee communication technology for processing.

The proposed method is then applied to classify the teachers' images. The dataset used in this research is custom-built and is comprised of images of 35 different teachers. Each image is labeled into one of eight distinct classes based on an evaluation of two key factors: the teacher's hand movements and their position within the classroom.

Finally, the details of the results of the teacher's teaching method are delivered to the educational supervisor through the Application layer. As a result, real-time feedback of the teachers' teaching style can be provided. Eventually, the education supervisor or any other person will be able to refer to it in the next stage of any decisions with minimal effort.

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