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Project-based learning for machine learning in computer vision courses: Case study of Kazakhstan and Slovakia

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Abstract

This study examines the effect of Project-Based Learning (PBL) on student motivation, engagement, and learning outcomes in the "Fundamentals of Machine Learning" course, focusing on computer vision applications. The research was conducted among third-year bachelor students in information technology programs. An experimental group, divided into four teams, implemented machine learning projects using TensorFlow, Keras, OpenCV, and DeepFace. Their results were compared with a control group following a traditional lecture-based approach. The experimental group showed a 60% increase in subject-specific motivation and a 55% rise in general learning motivation, significantly surpassing the control group. Post-test scores improved by 54% in the experimental group, contrasted with a 4% improvement in the control group, demonstrating that active, project-based activities boosted both theoretical and practical understanding of machine learning concepts. The results confirm that PBL fosters heightened enthusiasm for programming, deeper comprehension of machine learning models, and enhanced problem-solving skills in computer vision tasks. The study recommends broader adoption and further optimization of PBL approaches in technical education to increase student engagement, strengthen learning outcomes, and align coursework with real-world machine learning challenges.

Keywords: Computer vision, Higher education, Project-based learning, Student engagement, Student motivation.

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1. Introduction

Enhancing the effectiveness of research activities is a priority for both the professional community and governmental bodies. As society transitions to a high-tech economy, there is a growing demand for specialists who are not only equipped with professional knowledge and skills but also possess the ability to engage in scientific and creative research. These specialists must adapt swiftly to the ever-evolving scientific and technological landscape. Achieving high-impact outcomes necessitates meticulous planning of research and experimental work, with particular attention to the conditions under which such work is conducted [1, 2].

Project-Based Learning (PBL), alongside research, production-based science, and organizational and pedagogical activities, is recognized as a primary professional activity within national educational and professional standards. This underscores the competencies expected of university graduates, making the cultivation of project competence a core goal in higher education. PBL fosters this competence through autonomous student activities that involve creating novel materials or conceptual objects. It integrates theory and practice, employs a systemic approach to problem-solving, and encourages comprehensive processes such as modeling, planning, and forecasting [3, 4].

Project-based activities can be integrated into structured courses using active learning methods, as well as through diverse projects in both classroom and extracurricular settings [5, 6]. The PBL approach is active, student-centered, and problem-centered, typically involving small groups that encourage independent thinking and creativity. In computer science and engineering (CSE) education, PBL has emerged as a highly effective pedagogical strategy for enhancing students' teamwork, creativity, and real-world problem-solving abilities [7-10].

Previous studies have highlighted the benefits of PBL in various contexts. For instance, Arbelaitz, et al. [11] introduced PBL features that develop technological, curricular, and pedagogical supports to engage students in computational thinking through modeling [11]. Similarly, Johnson [12] discussed how PBL can improve students' engineering application and innovative abilities [12]. Despite these advancements, there remains a need to explore the specific impact of PBL on student motivation within machine learning education in the Kazakhstani university environment.

The primary aim of this research is to investigate the influence of the PBL method on student motivation in enhancing the theoretical and practical foundations of machine learning in higher education institutions. Specifically, this study seeks to address the following questions:

- *What impact does the implementation of Project-Based Learning (PBL) have on increasing student engagement, motivation, and learning effectiveness?*
- *How does the application of advanced learning techniques through PBL in areas such as facial emotion recognition, age, gender, and race within computer vision training compare with traditional training methods?*

We hypothesize that active student participation through a project-based learning approach will lead to increased motivation to apply machine learning models and a deeper understanding of key concepts in computer vision projects. Consequently, students are expected to exhibit greater enthusiasm for design and programming, alongside the development of practical problem-solving skills.

The subsequent sections of this paper are organized as follows: Section 2 reviews key literature relevant to the research topic; Section 3 details the methodology, including data collection and experimental setup. The results and discussion sections interpret the study’s findings, examining their alignment with or challenges to existing research in the field.

2. Literature Review

2.1. Face recognition

Facial emotion recognition is a challenging problem that has attracted significant scientific interest in the past few years and is currently one of the most discussed topics in the field of machine learning. Many previously difficult problems can now be solved by training machine learning models to recognize objects and faces. To this end, the machine learning architectures that underpin this rapidly evolving field, such as classification, measurement, detection, segmentation, representation, generation, counting, and more, are intuitively explained. In addition to the formation of theoretical and practical knowledge, an in-depth study of the machine learning module was planned [13]. Recognizing emotions in images or videos is a trivial task for the human eye, but very difficult for machines and requires many image processing techniques to extract facial features. Artificial intelligence, machine learning, and computer vision technologies are driving digital devices used in the study of emotions and behavior [14]. Human emotion detection has been implemented in many areas where additional security or information about a person is required [15]. This can be considered the third stage of face detection and recognition, where we may need to establish a third level of security, where along with the face, emotion types are also detected [16-18].

Rehman [6] in their research proposed a driver facial fatigue detection system using the most popular computer vision libraries, OpenCV and Dlib. The experimental results show that the HOG + Linear SVM face detector has 97.44% accuracy in detecting fatigue, and the MMOD CNN face detector has 97.90% accuracy in detecting face masks. The system effectively warns drivers of possible accidents in various situations, such as when turning on lights and wearing glasses. Dlib is a modern cross-platform C++ library known for its data structure manipulation, machine learning, and image manipulation [19]. OpenCV is an open-source computer vision and machine learning library. It is a general computer vision framework with over 2,500 optimized algorithms and many built-in features. Keras is a Python interface to an open platform for neural networks that serves as an interface to TensorFlow [20].

The prospects for the development of biometric systems and their effective use in any field are considered in research by many domestic and foreign scientists. In particular, Aitulen, et al. [21] presented the results of an experimental study to evaluate the effectiveness of the proposed approach in terms of face recognition accuracy using Principal Component Analysis (PCA) to construct EigenFaces for each class of facial features. Le Ngo, et al. [22] can classify human emotions such as fear, hate, disgust, anger, surprise, sadness, joy, and neutral. These emotions are very sensitive, and the contractions of the facial muscles are very small; detecting differences in these features can be very difficult since even a small difference results in different facial expressions. Research has shown that although we can only focus on the areas of the face that express emotion, around the mouth and eyes, how we make these gestures and how we categorize them is still an important issue.

In addition, Rajesh and Naveenkumar [23] highlight that for different or even the same emotions can vary depending on the reduction of facial features of people, since emotions depend on the context. Kenzhegulov and Serikov [24] formulated a comparative study of algorithms used in face recognition Kenzhegulov and Serikov [24]. Bosch, et al. [25] described detecting students' emotions in a game during a lesson using facial recognition using machine learning. In addition, Tsai, et al. [26] discuss a real-time face recognition system using SSD models, VGG-Face.

Facial recognition systems usually recognize basic emotions such as fear, anger, joy, surprise, sadness, and contempt. Basic emotions also include neutral emotions, that is, the concept of natural facial expression without any emotional expression [27]. But in real life, the spectrum of human emotions is not limited to a fixed set of basic facial expressions. Moreover, the possibility of using such sets is complicated by the fact that a person can express mixed emotions, for example, a mixture of joy and surprise. In this case, the emotion detection system can react by choosing the emotion that is expressed to the greatest degree, or by choosing a set of intensity ratings for each basic emotion separately.

King, in his study, implemented facial recognition in Python using the utility module dlib and OpenCV. Dlib is a well-known, modern, cross-platform C++ library for machine learning and image processing, featuring a pre-trained face detector that uses 68 positions (x, y) to predict the location of facial features on a person's face. It is known that the study of human emotions and behavior through the analysis of data is carried out using a facial algorithm to capture the features of the face, and in combination with machine learning, to identify and analyze the results [28].

For this reason, computer recognition of emotions is a complex task that can be solved by identifying the desired emotions experienced by people, as well as determining which technologies are best suited for their capture and which models and algorithms are the most effective. This is a very difficult task for specialists in computer vision for all volume matrix data [29].

Typically, facial recognition algorithms are applied to an image or captured frame before extracting facial features to determine the emotion, age, gender, and race of the facial expression. Then we can summarize the following stages of identifying emotions as follows:

1) Preliminary processing of the data set.
2) Face detection.
3) Feature extraction
4) Classification by features [30].

Ghofrani, et al. [31] in their study, consider the problem of facial expression recognition, which includes two stages: face recognition and emotion recognition [31]. In the first step, they use MTCNN to accurately detect edge boundaries with minimal residual edges. In the second stage, the ShuffleNet V2 architecture is used, which allows to provide a balance between model accuracy and speed depending on the user's situation. The results of experiments clearly show that the proposed model outperforms existing methods on the FER 2013 data set provided by Chiurco, et al. [32] in a joint study tested a deep learning model and a convolutional neural network (CNN) for emotion recognition during the development and testing of FER algorithms with the idea of facilitating human-robot interaction in assembly systems based on real-time detection of workers' emotions, and, as a result, the accuracy of the algorithm DeepFace, as established during the experiment, shows the highest 97% [32].

2.2 The Role of the PBL Method

PBL uses professional theoretical knowledge and practice, with the specific teaching aim of designing products that are closely related to engineering practice. Students work in groups to formulate project plans and implement them through discussion and communication. In completing projects, students learn and apply new knowledge through 'learning by doing' to improve their engineering application and innovation abilities. PBL is student-centered, encouraging enthusiasm and initiative in learning, and cultivating engineering design and scientific thinking abilities [6, 33]. The PBL educational philosophy runs through the entire course teaching process, including content teaching, project training, and extended application.

With the rapid development of internet and information technologies, many kinds of teaching modes have been introduced in class. The traditional teaching mode is transformed from face-to-face teaching to online teaching in times [34] . Due to the COVID-19 pandemic, face-to-face courses in most of educational institutes have changed to online courses[35]. Teaching modes such as online-offline mixture, SPOC, or MOOC are widely conducted in courses for improving teaching effects.

The PBL methodology has a great capacity to address varied problems in engineering: design of software systems Hurtado, et al. [3] and Marques, et al. [36] electric systems Muoka, et al. [37] microelectronics Garduño-Aparicio, et al. [38] and Gómez-de-Gabriel, et al. [39] medical applications Tsubota, et al. [40] structural engineering Justo, et al. [4] and mechatronics [41].

The potential of project-based learning (PBL) in computer science (CS) education has gained recognition in recent years, especially as a pedagogical tool to bridge the gap between theoretical knowledge and practical skills. A substantial body of research supports the effectiveness of PBL in enhancing students' engagement, critical thinking, and independent learning skills, which are essential for developing competencies in fields like computer science and software engineering [7, 9, 10, 42, 43]. The integration of PBL into curricula aligns well with constructivist theories of learning, which posit that students build knowledge through hands-on activities that connect new concepts with prior understanding.

Studies on implementing PBL in higher education institutions, such as Israel's revamped CS curriculum, indicate that incorporating final projects instead of traditional exams can lead to a more profound understanding of subjects by requiring students to apply their learning in real-world scenarios. This approach also enhances the development of essential skills in project management, problem-solving, and independent learning, preparing students for the demands of the technology industry [44, 45]. Table 1 below compares traditional problem-solving methods with project-based learning (PBL) in computer science education.

Table 1.
Traditional problem-solving methods VS project-based learning (PBL) in computer science education.

Aspect	Traditional problem solving	Project-Based Learning
Problem selection	Problem chosen by the teacher.	Problem selected by the student.
Problem definition	Defined by the teacher.	Defined by the student.
Uniformity of Problems	The same problem is assigned to all students.	Unique problems are assigned to each student.
Scope of Knowledge	Focus on specific CS knowledge.	Requires broad CS knowledge.
Type of Knowledge	Based on familiar or general knowledge areas.	Engages with unfamiliar and interdisciplinary areas.
Teacher's role	Teacher has predefined solutions.	The teacher collaborates with students to solve unique challenges.
Technical challenges	Few technical problems involved.	Involves numerous technical challenges.
Duration	Short-term tasks	Long-term, sustained project work.
Development complexity	Focus on individual programming modules.	Integrates multiple programming components.
Evaluation method	Assessed through traditional testing.	Assessed through alternative methods, often based on project output and process.

Source: Kokotsaki, et al. [46].

For example, in a meta-analysis of 55 studies, it was found that the PBL method has a positive effect on the motivation and activity of students, mainly aimed at various fields of science [47]. Likewise, the academic computer science community views group project work as an important component of any degree. Professional communities in the discipline around the world view project and group work as preparation for professional practice. PBL focuses on curriculum outcomes through a teacher-facilitated strategy, promoting active student participation, enhancing knowledge, project management skills, and collaboration, while providing tasks inclusive of all students, ultimately aimed at specific product development [48].

According to Scherz and Polak [49] learning through hands-on, project-based assignments is important in many areas of computer science education, including the fundamentals of machine learning. It is necessary to develop skills in designing and implementing systems in the field of computer science. The optimal approach is to use the PBL method when solving case studies. Students learn to solve real, complex problems rather than academic, simplistic problems while developing individual, hands-on learning and teamwork skills. These goals are supported by many engineering curriculum projects, such as the 2001 IEEE/Association for Computing Machinery (ACM) Computer Curriculum and Accreditation Institutions. Effective teamwork, responsibility and initiative are among the qualities typically required of leaders in this field. To achieve these goals, practical tasks and PBL methods that require students to design realistic real-world systems are sufficient [5].

Moreover, the cooperation among students for Francescato, et al. [50] is a powerful tool in complex environments and develops learning abilities and professional skills among students. The traditional teaching methods limit the movement of students: indicate the dramatic change in the learning environment and the participant requirements at the classroom with active methodology techniques.

The teaching of engineering and sciences through the creation of a functional product should improve by using the main characteristics of the PBL methodology.

(1) Small student work groups, most of the time, operate without the presence of a tutor.
(2) Realistic, professional, and large-scale tasks.
(3) Tasks that cover only a small part of the class content.
(4) Reading to deepen the technical content.
(5) Group work oriented toward a product.
(6) Learning new knowledge and abilities.
(7) Dividing tasks to obtain better products.
(8) Improving abilities that are strongly interrelated with other courses from the training.
(9) Focusing on the project work and less on the class.
(10) Individual responsibility is critical for project development.
(11) Assessing the final developed product.

The application of the PBL methodology transforms the professor's role, which is to guide workgroups. The obtained knowledge and skills are required for self-management, teamwork, leadership, time management, communication, problem-solving, and the ability to use technology-based tools.

3. Materials and Methods

3.1 Data Collection

The study was conducted during the 2023-2024 academic year in higher education institutions located in Astana, Atyrau, and Bratislava. A total of 84 students participated, representing a diverse and balanced sample. Of these, 32 students were part of the experimental group studying the course "Machine Vision Algorithms Training," while 41 students in the control group attended the course "Fundamentals of Artificial Intelligence and Robotics Systems" at Atyrau State University. Additionally, 11 students from Ekonomická univerzita v Bratislave joined the control group.

The experimental component was integrated into the "Fundamentals of Machine Learning" course, targeting third-year students enrolled in the "6B01511 - Informatics" program at L.N. Gumilyov Eurasian National University (ENU), the "6B01503 - Informatics and Information and Communication Technologies in the Educational System" program at H. Dosmukhamedov Atyrau State University (ASU), and the "7M06101 - Information Systems: Image Recognition Technologies" program. Additionally, students in the "Artificial Intelligence Systems and Fundamentals of Robotics" program participated in the study, engaging in experimental lectures, practical exercises, and independent assignments. Data collected during the study were analyzed, and the results are summarized and illustrated in Figure 1.

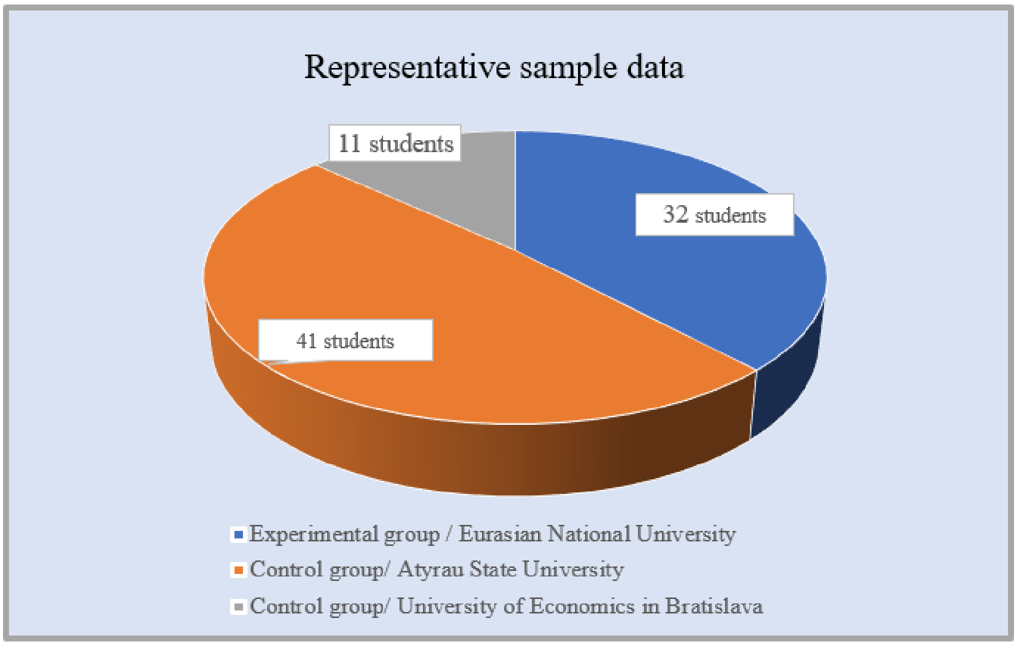

Figure 1.
Representative sample data.

3.2. Teaching Structure and Project Content

The course is a 3-credit hour technical elective, requiring a foundational course in signals and systems as a prerequisite. Students are expected to have some prior programming experience. Multiple textbooks were recommended as references, but none were mandatory, as students could rely on the instructor's notes for coursework. The class meets three times a week for 50-minute sessions, which are divided into three main formats: lectures, project discussions, and project labs. During lectures, the instructor delivers new concepts and fundamental topics in a traditional format. Project discussion sessions are used to introduce project details and clarify submission requirements, allowing students to ask high-level questions or propose modifications to project guidelines. Project lab sessions take place in a computer lab, where students actively work on their projects. In these labs, the instructor provides support by monitoring progress and answering technical questions.

Across the universities, the "Fundamentals of Machine Learning" course addressed key areas such as machine learning paradigms, classification, clustering, neural networks, and the use of open datasets. Hands-on sessions employed Python for statistical forecasting and data visualization. The modules "Image Detection and Recognition," "Face Detection and Recognition," and "Emotion Recognition from Faces" were introduced via a group-based, project-oriented learning approach. These projects made use of advanced libraries and frameworks such as MTCNN, FER, Keras, TensorFlow, OpenCV, Dlib, and DeepFace.

Students worked on their projects either in the cloud using Google Colab or locally with the Spyder IDE from the Anaconda distribution. Spyder's feature set (including a code editor, IPython console, variable manager, and graphical debugger) proved instrumental in streamlining the learning process.

3.3. Stages of Project-Based Learning

In this study, participants were split into four groups through a randomly generated process using an online tool, ensuring an equitable distribution of varied skill levels and prior knowledge. Once groups were established, students were introduced to the Project-Based Learning (PBL) framework, based on the primary stages described by Vallera, et al. [51]

1. Introducing fundamental concepts and skills,
2. Introducing core content and skills,
3. Emphasizing essential foundational knowledge,
4. Fostering critical thinking, problem-solving, and collaborative skills,
5. Supporting independent research,
6. Providing ongoing feedback, and
7. Delivering the final project outcome.

The group projects aimed to provide hands-on experience with state-of-the-art machine learning techniques while enhancing collaborative, technical, and research skills. By focusing on different facets of computer vision, the projects exposed students to diverse methods and tools for solving real-world problems.

3.4. Project Descriptions and Expected Outcomes

Each group was assigned a specific project topic that involved various machine learning libraries and algorithms. Table 2 presents the expected learning outcomes, assigned tasks, and evaluation criteria for each project.

Table 2.
Expected project outcomes, tasks, and assessment criteria.

Projects	Expected learning outcomes	Tasks evaluation
Project 1	Implement a facial emotion recognition program using the MTCNN method and the FER library in the Google Colab Notebook environment to work with Python code.	The student will implement a facial emotion recognition program using seaborn, matplotlib, face_recognition, mtcnn, FER
Project 2	Implement a facial emotion recognition program on the Anaconda distribution using the Spyder integrated development environment (IDE) in Python using TensorFlow, Keras, ".weights.h5".	The student will implement a facial emotion recognition program using HOG, keras, TensorFlow, numpy, facial_expression_model_structure.json facial_expression_model_weights.h5
Project 3	Implement a program for detecting the age and gender of students in the Anaconda distribution using the Spyder IDE in Python with HOG, OpenCV, and Dlib.	The student will implement a program for detecting the age and gender of students using OpenCV, Dlib, face_recognition, HOG, gender_net.caffemodel
Project 4	Implement a program for recognizing facial emotions, age, gender, and race of students in the Anaconda distribution using the Spyder IDE in Python with DeepFace.	The student will implement a program for recognizing the facial emotion, age, gender, and race of students using DeepFace.

Throughout the project, students received ongoing feedback based on specific task requirements. During the formative phase, performance assessments helped to identify students' problem areas, providing timely support. Group-based mutual scaffolding allowed students to learn collaboratively, gradually reducing external support as group members gained confidence in their project execution. By project completion, each group presented their work, followed by comparative analyses across groups, reinforcing knowledge acquisition.

The "Machine Vision Algorithms Training" course employed a blended approach, utilizing both online and offline resources. Offline classes were held in computer labs, while online sessions leveraged the Moodle learning platform. The PBL framework was structured into three phases—pre-training, in-training, and post-training—supporting the progressive development of students' skills and fostering diverse, individualized learning.

Pre-training involved preview materials on Moodle, with example projects such as "Beautiful Photo Show" encouraging student interest and preparation. In-training sessions combined online and offline components, including brief, targeted exercises. The teacher used Moodle to track student progress and provide real-time feedback. Post-training consisted of comprehensive projects combining software and hardware to encourage independent problem-solving. Final evaluations involved both teacher assessments and peer evaluations.

All procedures in the study adhered to ethical guidelines, ensuring that student participation was voluntary and that personal data was handled with confidentiality. Ethical approval was obtained from the ENU ethical commission.

4. Results and Discussion

In the next stage of our research, students in the experimental group were trained in four groups using the Computer Vision module and the Project-Based Learning (PBL) method. This training focused on utilizing machine learning algorithms in diverse environments to cultivate programming skills for emotion, gender, age, and race identification through facial expressions. Additionally, students deepened their knowledge guided by predetermined success criteria. The results of a brief analysis between groups were as follows:

4.1. Group 1 (MTCNN, Method FER)

This algorithm combined methods from the MTCNN and FER libraries to detect faces and emotions in photographs uploaded by a web camera. Based on this algorithm, students were able to enhance their knowledge in the interactive cloud environment Google Colab Notebook for working with Python code in the Google browser and create a program that recognized human emotions and constructed diagrams using the MTCNN method and the FER library. This project utilized MTCNN for face detection and the FER library for facial emotion detection, achieving good accuracy in emotion detection, as evidenced by the graphs in Figure 2. However, limitations were observed when analyzing other parameters such as age, gender, and race.

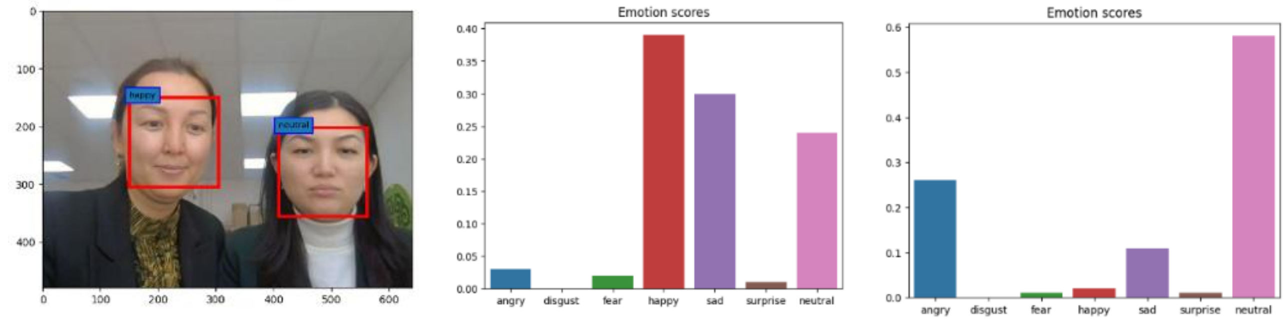

Figure 2.
Detection of faces, emotions and output data diagram (MTCNN, method FER).

4.2. Group 2 (Keras, tensor flow method)

This algorithm combined methods that used the HOG method to detect faces in a preloaded photo and the structure of a pre-trained facial expression model. The JSON model was pre-trained using Keras, a TensorFlow library for emotion detection and analysis, and pre-trained neural network weights in .weights.h5 saved models. Based on this algorithm, students learned to use the HOG method, Keras, TensorFlow libraries, and a pre-trained model of facial expression structure.json to create software for detecting human emotions in Spyder, an integrated development environment (IDE) that is part of the Anaconda platform for working with Python code. The neural network .weights.h5 was trained to use the stored weight models (Figure 3).

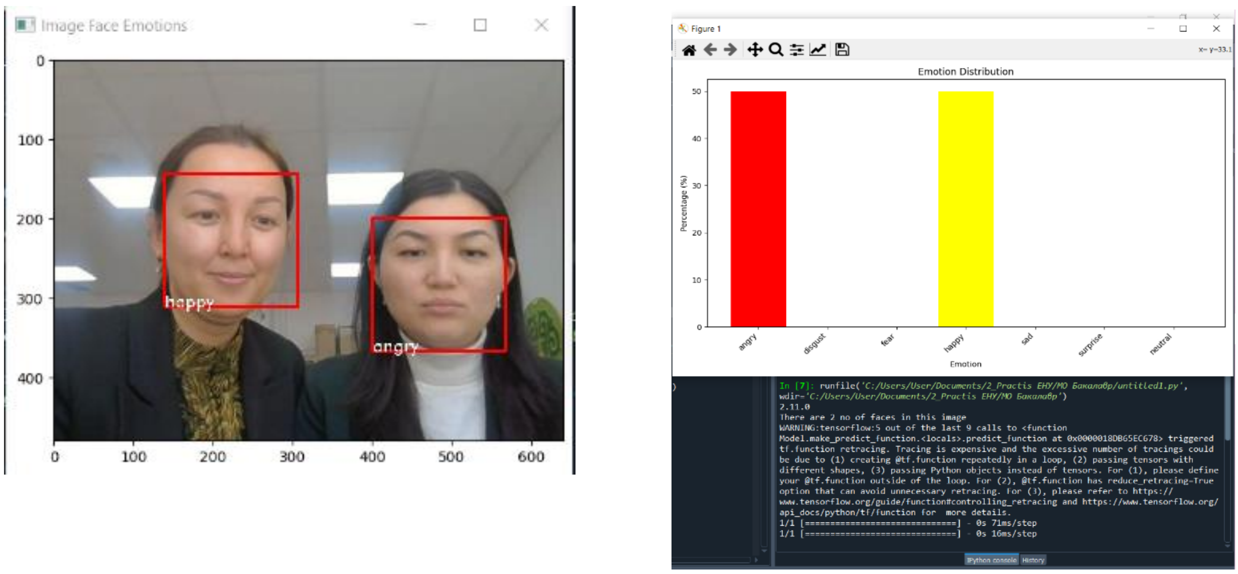

Figure 3.
Detection of faces, emotions, and output data diagram (Keras, tensor flow method).

4.3. Group 3 (OpenCV, method Dlib)

This algorithm combined the methods of using OpenCV, the HOG method for detecting faces in pre-loaded photographs, and the use of pre-prepared sample data gender_net.caffemodel, gender_deploy.prototxt, age net.caffemodel, age_deploy.prototxt to determine the gender and age of students. using the library Dlib (See Figure 4).

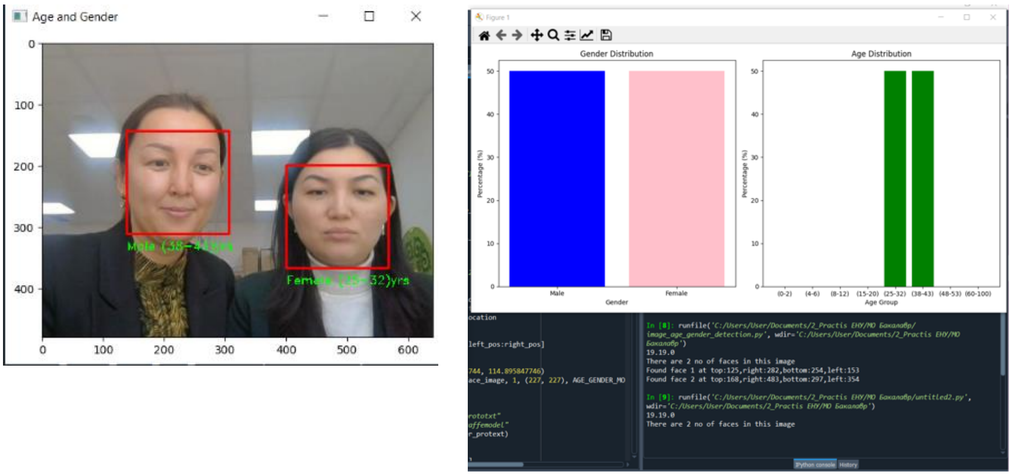

Figure 4.
Detection of faces, age, gender, and output data diagram (OpenCV, method Dlib).

Based on this algorithm, students learned to install OpenCV, utilize the HOG method, and integrate the Dlib library in Spyder, which is part of the Anaconda platform for Python code development. They also employed pre-prepared age and gender models to create a program for determining a person's age and gender (Figure 5). This project utilized OpenCV and Dlib to ascertain emotions, gender, and age from a face, providing ease of use and compatibility with video streams. However, limitations in accuracy were observed.

4.4. Group 4 (DeepFace method)

This algorithm combined the DeepFace method for recognizing faces from a pre-loaded photo with the method for determining emotions, gender, age, and race of students using the DeepFace library. Based on this algorithm, students analyzed images using deep learning neural networks DeepFace in Spyder, which is part of the Anaconda platform for Python code (Figure 5). They learned to create a program displaying results related to emotions, age, gender, and race on the screen for face 1 and face 2 (Figure 6, Figure 7).

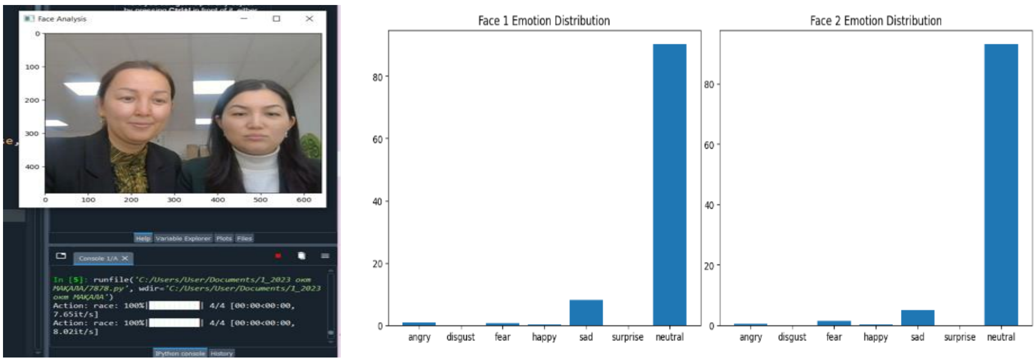

Figure 5.
Detection of faces, age, gender, and output data diagram (DeepFace method).

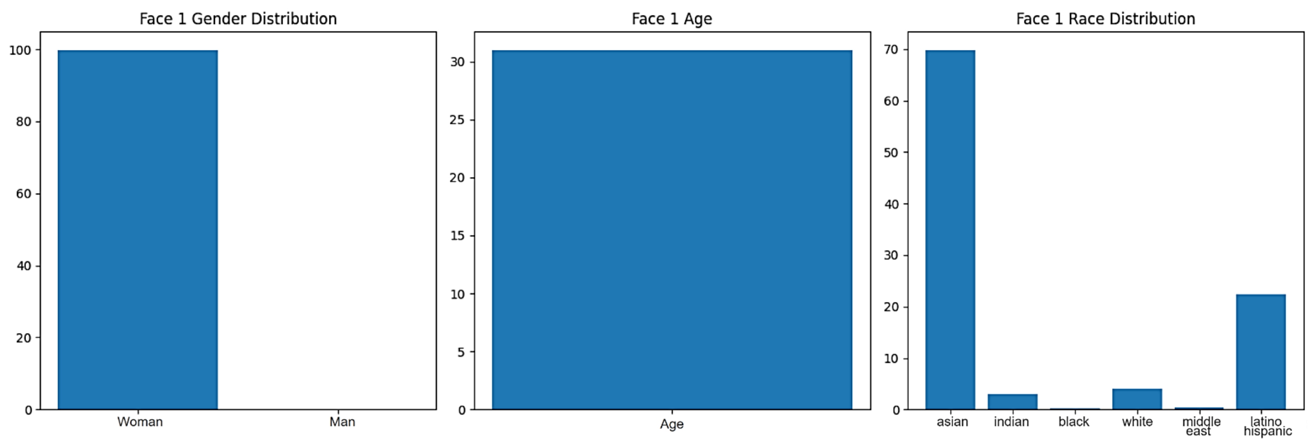

Figure 6.
Detection of age, gender, race, and output data diagram (Face 1).

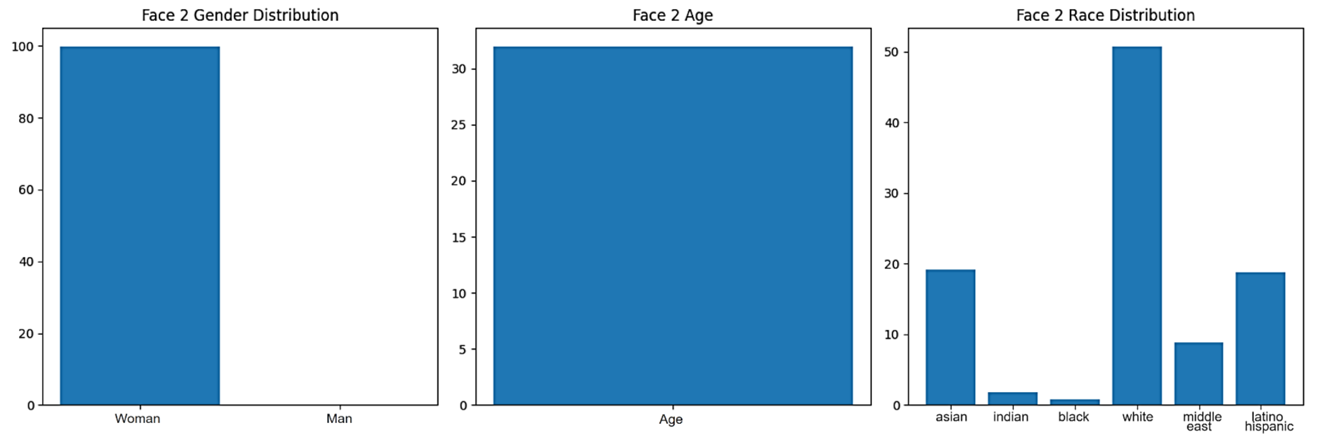

Figure 7.
Detection of age, gender, race, and output data diagram (Face 2).

4.5. Students' Feedback on the Course

Based on the results, the student groups compared their projects with the methods of other groups (see Table 3) and determined the advantages and disadvantages of each project.

Table 3.
Feedback on the results of the project according to the conducted studies.

Methods	MTCNN, FER	Keras, TensorFlow	OpenCV, Dlib	DeepFace
Required libraries	mtcnn, fer, face recognition, numpy, OpenCV	Keras, tensorflow, OpenCV	OpenCV, dlib, face recognition	deepface, OpenCV
Required volume of data	3589 pictures of 48*48 pixels.	36000 images of 48*48 pixels, .json 5Kb, .weights.h5 6Kb.	26580 images of 48*48 pixels, Caffe model 44Kb/44Kb	Contains more than 120000000 images.
Time spent testing	up to 1 minute	up to 1 minute	up to 1 minute	up to 5 minute
Accuracy	75-80%	70-75%	60-70%	90-95%
Benefits	Ease of use, the ability to identify several faces in one image, and high speed.	Uses deep learning to detect emotions, achieving high accuracy, the ability to detect several faces in one image, and high speed.	Uses deep learning to determine age and gender, has the ability to recognize several faces in one image, and operates at high speed.	Identifying emotions, age, gender, and race requires deep learning, facilitates visualization, and achieves high accuracy.
Drawbacks	Accuracy decreases in light or darkness, limited in the analysis of other parameters, such as gender and age.	Accuracy decreases in light or darkness, limited in the analysis of other parameters such as gender and age.	Limited in analyzing other parameters such as emotions, and it does not provide an interactive user interface, resulting in low accuracy.	very low speed, high hardware requirements

The most significant difficulty was reported in the stage of "Classification according to the Characteristics," accounting for 30% of the responses. This was followed by "Dataset Preprocessing," which posed challenges for 22% of students. Issues related to "Install and Import Required Libraries" were noted by 17% of participants, while 15% experienced difficulties in the "Step of Emotions, Age, and Gender Detection." Creating a function to take a photo presented challenges for 11% of students, and the "Step of Faces Detection from an Image" was the least problematic, with only 5% reporting difficulties. It was noted during the session that preparing a preliminary video guide for these steps in future sessions would be beneficial. Providing such guidance would enable each group to complete projects more effectively after receiving specific feedback and clarification.

The subsequent stage of the study involved evaluating the effectiveness of the Project-Based Learning (PBL) approach by assessing students' motivation. The evaluation was based on a set of predefined criteria established within the framework of a motivational assessment matrix (refer to Table 4).

Table 4.
Comparison of the results of the project according to the conducted studies.

Name of indications	Indications
Self-initiative	The extent to which students take initiative in the learning process, such as asking questions, suggesting project ideas, or seeking additional resources.
Active participation	Active participation and engagement in class activities, discussions, and group work related to the project.
Responsibility for learning	Taking responsibility for your learning process, setting personal learning goals and monitoring progress towards them.
Collaboration skills	Effectiveness in collaborating with team members, sharing ideas, delegating tasks, and constructively resolving conflicts within the team.
Motivation for the subject	Showed particular interest and enthusiasm for the topic raised in the project, which was confirmed by active participation.
Motivation to study	General motivation for learning, includes internal motivation (interest, pleasure) and external motivation (rewards, grades, recognition).

A framework for categorizing students' levels of motivation involved three tiers:

- *High Level 85-100%*

Students demonstrate high levels of motivation, actively participate in the learning process, demonstrate enthusiasm for the subject, and consistently exhibit behaviors associated with high motivation.

- *Average 40-84%*

The student demonstrates a moderate level of motivation, participates adequately in activities, and shows some interest in the subject matter, but may not always exhibit a high level of activity or initiative.

- *Low 0-39%*

Students demonstrate low levels of motivation, show minimal interest or engagement in the learning process, have difficulty maintaining concentration, and exhibit little enthusiasm for the subject.

Using a system of predetermined criteria for assessing student motivation, schematic assessment results were summarized. The comparative diagram clearly shows that after the introduction of the project-based teaching method in the experimental group, the motivation for the subject increased by 60%, and motivation to study increased by 55% compared to the control group (Figure 8).

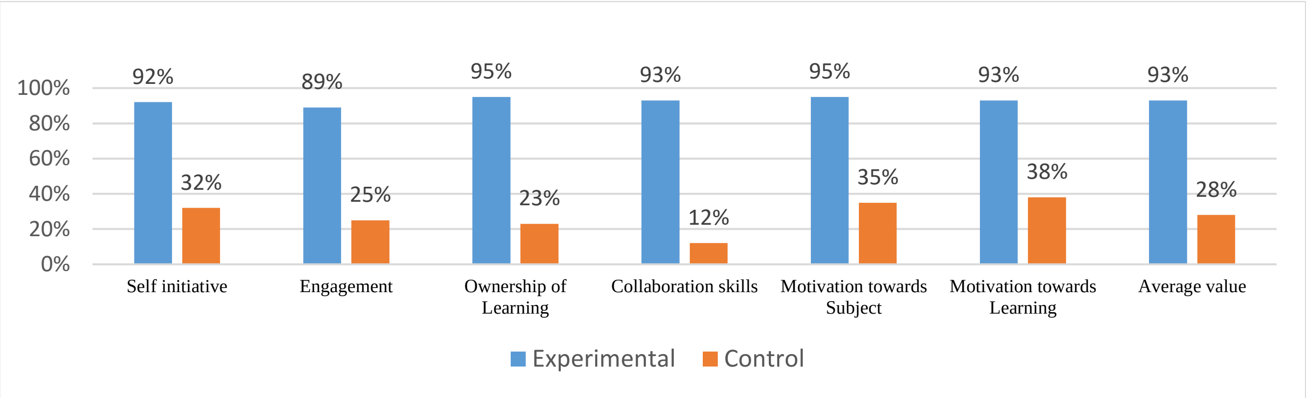

Figure 8.
Assessment of student motivation in the use of PBL: comparison by criteria

Overall, students expressed satisfaction with the lessons, citing clear explanations, engaging activities, and effective organization (Figure 9).

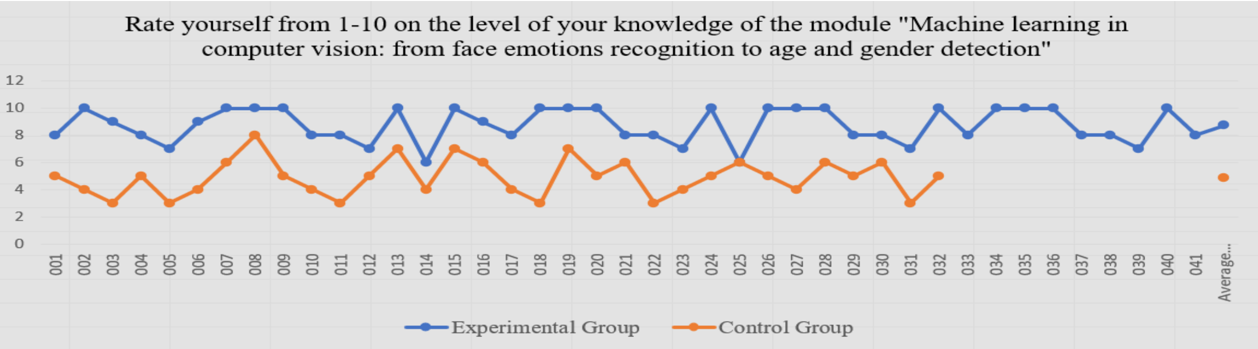

Figure 9.
Answers to the question "Rate yourself from 1-10 on the level of your knowledge of the module "Machine learning in computer vision: from face emotions recognition to age and gender detection""

The comparison between the experimental and control groups shows a notable difference in the improvement of students' performance. While the experimental group achieved a significant increase in the quality of education by 15%, the control group showed only a modest improvement of 4% (Figure 10).

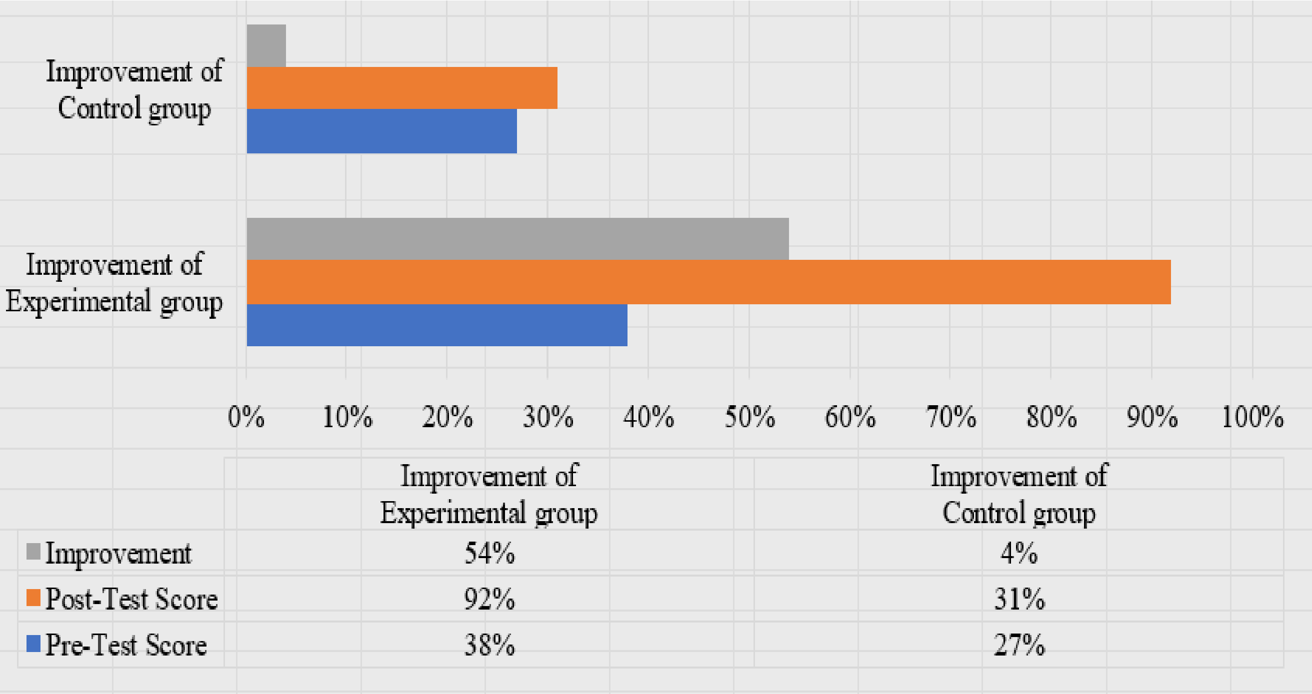

Figure 10.
Comparison of the results of the experimental and control groups

Figure 10 reveals a significant increase in educational outcomes, with most students demonstrating substantial improvements. For instance, Student ID 001 showed a 52% increase in knowledge, improving from a pre-test score of 41% to a post-test score of 93%. Similarly, Student ID 003 experienced a remarkable 69% improvement, rising from 25% to 94%. The average pre-test score across the group was 38%, which increased to 92% in the post-test, resulting in an average improvement of 54%. Individual improvement rates varied, with the highest recorded improvement being 80% (Student ID 027) and the lowest being 25% (Student ID 013). Visualization of academic performance statistics for the experimental group is depicted in Figure 11.

Figure 11.
Visualization of academic performance statistics for the experimental group.

This highlights the greater effectiveness of the Project-Based Learning (PBL) method employed in the experimental group, suggesting that it had a more substantial impact on enhancing students' understanding and academic performance compared to the traditional teaching methods used in the control group, supporting the hypothesis of the research.

5. Conclusion

Drawing on our findings, we infer that incorporating the Project-Based Learning (PBL) model produced a distinctly positive influence on student motivation, participation, and overall academic achievement in machine learning instruction, especially in the domain of computer vision. A thorough examination of PBL's utility addresses our primary research questions and corroborates the underlying hypothesis.

RQ1: *How does introducing Project-Based Learning (PBL) enhance student engagement, motivation, and overall learning effectiveness?*

Our investigation reveals that PBL markedly increases student engagement, motivation, and performance. Learners in the experimental group displayed a significant boost in drive: a 60% surge in course-specific enthusiasm and a 55% rise in general motivation. Additionally, these students attained a 15% improvement in academic quality, whereas the control group reported only a 4% gain. On average, knowledge acquisition in the experimental group climbed by 54%, with pre-test scores moving from 38% to 92% at post-test. Respondents consistently praised the course's design and content, highlighting the stimulating activities and well-structured curriculum. Collaboration and active participation were strongly encouraged, and participants tackled project hurdles by drawing on teamwork and constructive critique.

RQ2: *How does examining advanced learning methodologies via PBL for facial emotion recognition, age, gender, and race detection in computer vision compare with outcomes from conventional training methods?*

Our analysis points to the transformative role of PBL in computer vision education, particularly concerning facial emotion, age, gender, and race detection. By directly engaging with machine learning tools such as MTCNN, OpenCV, and DeepFace, learners in the experimental cohort refined their programming skills significantly. The structured PBL format prioritized hands-on involvement, prompting students to incorporate pre-trained models, fine-tune algorithms, and confront real-life scenarios. Throughout these projects, participants strengthened both technical expertise and collaborative abilities by working in teams and solving challenges independently. Despite variations in project complexity, every group interacted with state-of-the-art technologies, fostering an atmosphere of innovation and exploration. Learners noted that the program successfully balanced theoretical foundations with practical application. Confronting tasks like data preprocessing and classification built resilience and adaptability, while the reflective nature of PBL deepened their grasp of how theoretical concepts translate into tangible results.

Although PBL delivered many advantages, several limitations emerged. Resource-heavy methods like DeepFace required powerful hardware and large datasets, creating barriers for students with limited computing capacity. Testing durations also varied, with DeepFace proving more time-intensive compared to faster approaches like MTCNN. While MTCNN and FER excelled at emotion detection, they could not assess parameters such as age, gender, or race. Suboptimal lighting conditions weakened the accuracy of multiple models, diminishing their real-world utility. Students identified data preprocessing and classification as particularly demanding, time-intensive steps. A steep learning curve for frameworks like TensorFlow and Dlib presented initial obstacles for novices, and group work sometimes led to uneven contributions, affecting outcomes. Moreover, because the PBL framework heavily depended on instructor guidance, it proved resource-intensive. Lastly, the study's conclusions may be less applicable outside of computer vision or non-technical subject areas.

Looking ahead, the number of students per group will vary, and inter-group collaboration will be encouraged to gauge its effect on project results. These strategies aim to deepen our insight into how different team arrangements can optimize both quality and efficiency. A long-term review of the revised teaching methodology will assess its endurance and overall impact over time. Additionally, mini-projects will soon account for 30% of the final course grade, a shift that acknowledges both their complexity and the elevated student engagement they inspire. This modification reflects the value that students place on experiential, project-focused learning and is intended to further invigorate their commitment to the educational process.

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