International Journal of Engineering Education Vol. 36, No. 6, pp. 1773–1782, 2020
Printed in Great Britain
0949-149X/91 $3.00+0.00

A Project Based Learning Approach for Teaching Artificial Intelligence to Undergraduate Students*

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This work presents an active learning methodology called Project-based learning (PBL) for developing artificial intelligence (AI) in a computer vision course of an undergraduate engineering degree. The objective of the course was to develop image recognition capabilities using Deep Learning (DL)/Machine Learning (ML) technics in real-world problems. The PBL learning methodology helped students search for real-world problems, develop complex solutions, and generate synergy among team members. The main role of the professor was to advise, guide and motivate the students throughout the course. The pedagogic innovation with active learning methodologies offered the professor the opportunity to create a dynamic motivating learning environment based on experiences. Each undergraduate engineering student had the opportunity to develop the skills and techniques of their profession: teamwork, proactivity, innovation, and leadership. The results obtained by the student teams showed problem-solving, including the use of automatic navigation equipment with AI, detection of the malaria parasite, recognition of non-human individuals to control vehicular traffic.

Keywords: artificial intelligence; artificial neural network; image recognition; machine vision; project engineering

1. Introduction

Learning AI technics establishes new challenges to teaching at the university level. Technological changes reduce the life cycles of products and services [1]; The professor and the students must incorporate new technics to their competences during the elective period. [2] presented the PBL methodology for learning computer vision: its main advantages are associated with motivating students to undertake individual and team-based learning, the discovery of new concepts, and the capacity to

* Accepted 5 May 2020.

develop real-world problems by presenting a simple problem [3].

The weaknesses of the PBL methodology regarding the difficulty to establish levels of compromise and learning with all students are mentioned in [4]. However, the PBL methodology [5–12] characteristics are defined by a variety of components and reduce the desertion, lack of motivation, or self-esteem of the students [13–16]. The components of the PBL philosophy established by the authors [17–19] are (1) define a problem starting point, (2) organize the projects, (3) define the teams, (4) guide or advise the participants – by the professor –, and (5) establish interdisciplinary learning.

The PBL methodology has a great capacity to address varied problems in engineering: design of software systems [20–24], electric systems [25–28], energetic systems [29, 30], microelectronics [31–33], medical applications [34, 35],structural engineering [36, 37] and mechatronics [38, 39].

The capacities of the university laboratories allow engineering students to develop and implement complex Works. Over the last years, DL/ML technics have allowed images of the multiple databases to be identified and classified accurately [40, 41]. The selection of the image classification technique must consider the response times, the accuracy of the image or video categorization, the energy expenditure, and the image size and analysis method [42]. The image recognition techniques recognised for their precision and analysis speed are YOLO [43] and single shot detector (SSD) [44] based on end-to-end algorithms, and the region proposal method with convolutional neural networks (CNNs) [45].

The authors of [10, 46–49] present works undertaken by undergraduate students through the integration of educational objectives of science, technology, engineering, and math (STEM). The support of experts allows teams of motivated students to be developed, using easy access technological capacities such as Raspberry [50], Python [51], and low cost sensors and controllers [52]. Some complex problems addressed in these semester courses are autonomous drones [53], robotic arms with AI [46], and DL for classification of image data bases [54–56].

2. Materials and Methods

The cooperation among students for [57], 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: [57] 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, without the presence of a tutor, (2) realistic, professional and large magnitude tasks, (3) tasks that cover only a small part of the class contents, (4) reading to deepen the technical content, (5) group work oriented towards 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 – critical for project development –, and (11) assessing the final developed product [58–60].

The application of the PBL methodology transforms the professor's role, which is to guide workgroups. [61] points out the need to perform large scope work focused on the student, with collaborative workgroups to solve real-world problems. The obtained knowledge and skills are required for self-management, teamwork, leadership, time management, communication and problem-solving, and the ability to use technology-based tools [62–65].

This model allowed responsibilities to be assigned to different student groups, who are transformed into active actors of their education [66–68].

The project approach – disintegrating the project into delimited problems- facilitates teamwork, creates task specialization, and increases the depth of the content applied by the teams [69–71].

The final objective of the course is to establish a work team, search for a real-world problem and solve it using DL/ML technics for the classification of images. The project was addressed from the engineering perspective, developing (1) the design and engineering of the product, (2) the technical studies, (3) the software engineering (4) the prototype and (5) the functional tests of the product [72–74].

2.1 Course Description

During semester planning, the third-year AI class was considered, supported by one professor and two students in their last year of study. The activities were established on a schedule with weekly deliveries of convergent activities. This model allowed multiple activities to be performed in parallel; speeding up the project term [75, 76]. The student teams (3 to 5 people) could choose problems based on their technical abilities, skills, and intellectual interests.

The development of the course was performed in a laboratory composed of one computer per student. The DL technics were prepared and presented by the teams using the PBL methodology. Each exhibition was followed by a feedback activity from the professor and questions from the other teams. The weekly activity included a discussion regarding project portfolios and their possible technological solutions.

Finishing the first stage of 6 weeks, the teams presented their chosen project, the state-of-art of the problem, and the technics required for the solution.

During the second stage of the course, lasting 8 weeks, students established two forms of communication, (1) the communication between each team and the teacher to receive advise on the most difficult points of the project and (2) communication between all the teams and the professor in the classroom. This communication in classes is essential to ensure the delivery of all the technical course content, and peer learning; it is necessary to stimulate opinions among the groups to reduce the learning curve for project development.

Finally, in the third 2 week stage the students must validate their prototypes, deliver the project documentation and give a final presentation with a functional prototype.

2.2 Computer Vision Projects

The vision computer projects selected by the teams addressed a variety of problematics, from automation of naval autonomous equipment with AI, detection of the malaria parasite, and recognition of non-human individuals to control vehicular traffic.

All the teams presented their functional prototypes of image classification at the end of the course.

3. Result and Discussion

Over this last decade the advances in the design and construction of autonomous marine robots improved substantially for the application to exploration, oceanographic science, and marine engineering. The remote vehicles must be controlled by human operators in real time. This work is laborious and repetitive: the operators must be highly trained to face complex trajectories and recognize the marine environment [45].

The autonomy of the marine equipment can be addressed using acoustic and visual sensors. The use of acoustic sensors is widely used in marine applications, however, the visualization of marine elements at close distances to the boat, require the use of visual sensors [77]. The use of the computer vision technique known as DL precisely identifies marine equipment, marine fauna, and landscapes.

Fig. 1. Prototype of a manned auto embarkation, fed through solar energy.

These visual sensors must have the capacity of image recognition based on vision computer technics [78, 79].

For the recognition of floating objects an open-source library for automatic learning – called TensorFlow – was used (version 1.7 compatible with operative systems of 64bits as Ubuntu 16.04), which can build and train neural networks. To initiate neural training the open-source model called MobileNet was used: it provides an efficient vision for mobile devices, using an entry resolution of 224 pixels and with relative sizes [80]. The technological solution was installed in a Raspberry Board to analyze the surroundings and command of the anti-collision system of the autonomous embarkation (Fig. 1).

3.1 Project Materials and Methods

The start of neural training was carried out on a Notebook Lenovo Ideapad 110 (Processor 2.5 GHz and storage capacity of 1 TB). MobileNet was set to select images of 224 pixels that even though they provide better resolution and require more processing time, will deliver higher classification accuracy. Acceptance of these images in relative sizes will be established in the settings.

Along with the setting process, the monitoring tool TensorBoard that comes incorporated in Tensorflow will also be activated. The selection of the neural network model was done by taking into account some restrictive system parameters with 1 Gb of RAM memory and a 32 Gb memory disk that comes in the Raspberry Pi-Plate [81, 82], to use the trained network with its updates. The selection of the Raspberry-MobileNet system is associated with low energy levels to detect objects in real-time.

The retraining is executed by loading the image

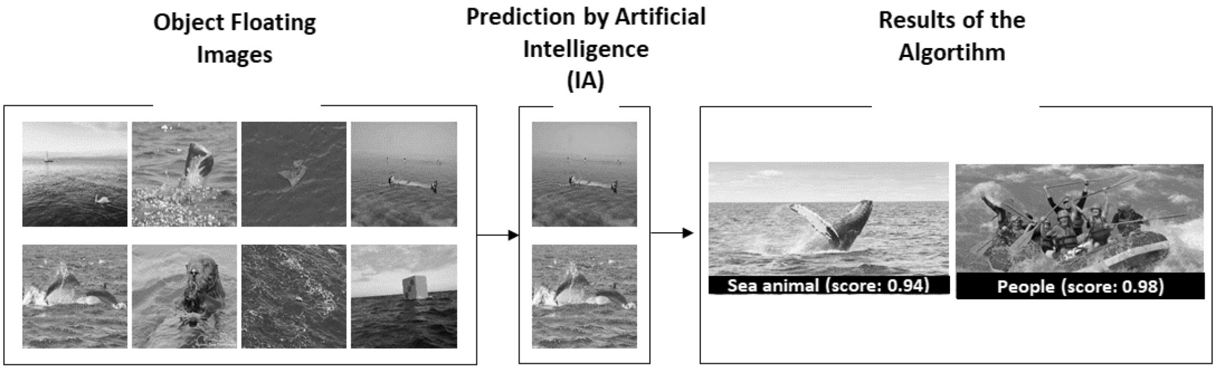

Fig. 2. Diagram of predictive model by artificial intelligence.

databases that were prepared for the initial layer. Considering restrictions of visible light from 500 to 700 nm, the position of the camera where the sun does not obstruct the image capture and the size/visibility of the object, excluding images during the night, with visibility below 400 nm.

Each category can contain a minimum of 20 images [83] (with no size distinction), in this case, a repertoire of 300 images was included in a category in ".jpg" format, obtained from "image-net.org" and from "google images", considering a training of 500 steps. Retraining can extend up to 4.000 iterations, this method is used to improve test performance; the results obtained in the training did not detect performance variations using both kinds of iterations.

Test procedure: for retraining the following stages were followed (Fig. 2): (1) retrain through the loading of images, (2) results of the neural training with categories included, (3) experimentation with external images to those used previously, (4) results of floating object recognition [84].

3.2 Project Results

In Fig. 3 and Table 1 the validation accuracy of the images or the percentage of images correctly labeled are displayed. The X axis shows training progress and the Y axis shows the accuracy for entry resolu-

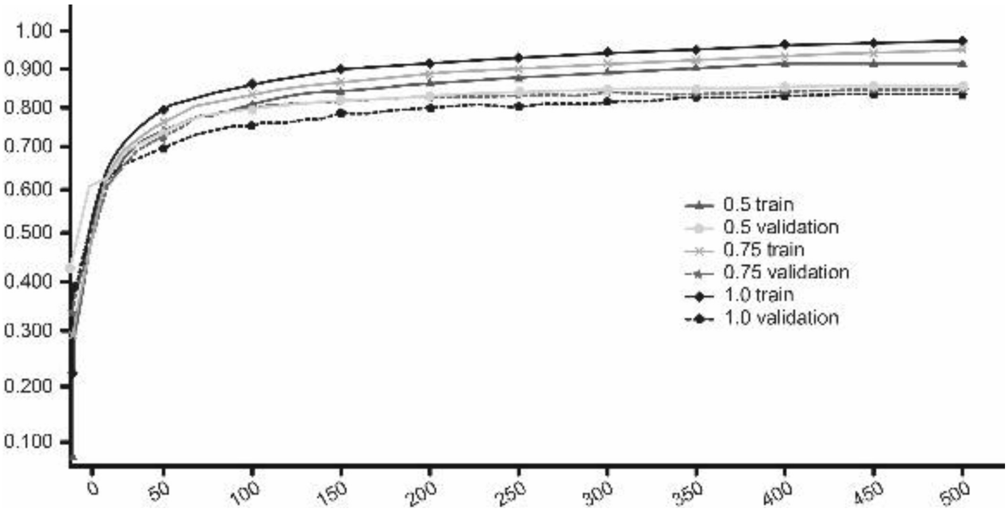

Fig. 3. Occurrence graphic by sizes relative to MobileNet.

Table 1. Accuracy data of the model

Name	Smoothed	Value	Step	Relative
Mobilenet 0.50 224/train	0.9195	0.9700	499.0	15s
Mobilenet 0.50 224/validation	0.8497	0.8500	499.0	15s
Mobilenet 0.75 224/train	0.9447	0.9800	499.0	15s
Mobilenet 0.75 224/validation	0.8439	0.8900	499.0	15s
Mobilenet 1.0 224/train	0.9716	0.9400	499.0	16s
Mobilenet 1.0 224/validation	0.8348	0.7900	499.0	156s

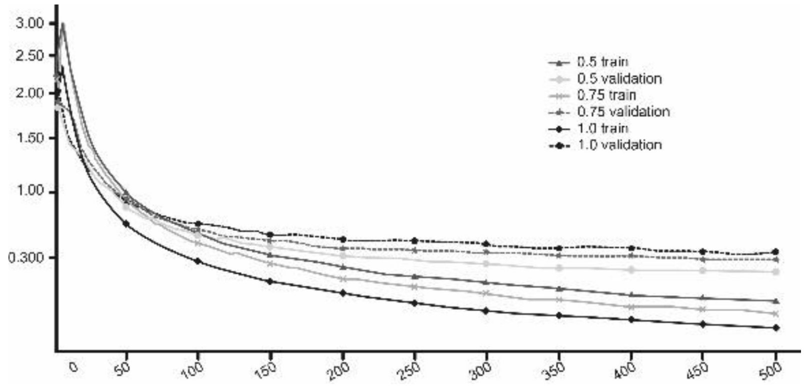

Fig. 4. Graphic of entropic cross by relative sizes at MobileNet.

tion at 224 pixels for the different relative sizes used in the training tests of floating objects (0.25, 0.50, 0.75 and 1.0).

The Train line presents the accuracy of the training data model, while the validation line shows the accuracy of the set of tests. For this case, the train graphics have an upward trend, while the Validation graphics are below them; the model is over adjusted and starts memorizing the training set instead of understanding the general patterns in the data.

For this experimental phase, the progress of the model's cross entropy must be analysed to understand the improvement of the learning process.

The objective of the training is to reduce the loss to ensure learning: keeping the declining trend through the discard of short-term noise.

The script executed 500 training iterations. Each step chooses ten images at random from the training set with its bottlenecks (penultimate layer responsible for classification) in the cache and introducing them into the final layer to obtain predictions. Those predictions are compared to the real labels to update the weights of the final layer through the backward propagation process. The repetition of the process improves the accuracy of the neural network. Once the experiment is finished a final evaluation of the test accuracy is performed with a set of new images. This test evaluation is the best performance estimation of the model trained in the classification task. The accuracy values vary between 80% and 95%. Each experiment modifies the predictive capacity due to the random character of the neural process in the selection of images. The results are represented in Fig. 4; in the X axis shows the quantity of iterations, Y axis the accuracy of entry resolution 224 pixels with the different relative sizes evaluated (0.25, 0.50, 0.75 y 1.0).

The great number of samples in the database provides the algorithm with a better opportunity to learn and provides a more specific database for training, which in turn allows the accuracy of the model to be improved [85, 86]. Finally, the obtained results with the modified CNN are compared with the results obtained using others benchmark CNN trained for the detection of floating and non-floating objects [87–89], obtaining improved performance in the recognition and classification of images. Table 2 presents the test results of the selected categories, which can be compared with the retraining results of a network, achieving better results than non-trained networks [90].

3.3 Project Discussion

We trained a CNN to detect floating objects in the sea for the navigation of a manned auto embarkation, powered by solar energy with a Raspberry

Table 2. Average percentage of the recognition assertiveness of objects for the applied methodology

Category	TensorFlow CNN retrain	MatLab	Inception	Yolo
Boat	0.9642	0.7595	0.3033	0.7420
Dock Maritime	0.8634	0.20000	0.5012	0.0000
Iceberg	0.9140	0.6000	0.0000	0.0000
Obstacle	0.9714	0.6000	0.0791	0.0000
People	0.9381	0.6800	0.0000	0.7960
Sea Animal	0.9675	0.8200	0.8376	0.0000
Submarine	0.9995	0.9195	0.4692	0.1200
Waterfowl	0.9724	1.0000	0.2720	0.8300
Eave	0.9714	0.4800	0.3508	0.0000

Table 3. Results of students self assessment using five-point Likert surveys of master class learning group (35 students) and the PBL group (42 students)

Question	PBL Mean	Master Class Mean
Did you apply your abilities of abstraction, analysis, and synthesis during the development of the project?	4.3	4.0
During the development of the project, did you delve into knowledge and experience of the study and profession field?	4.0	3.5
During the development of the project, did you improve the way you communicate in another language?	3.0	1.5
During the development of the project, did you develop your abilities to use technology and communication tools?	4.8	4.5
During the development of the project, did you increase your ability to search and analyze information from several sources?	4.3	2.5
During the development of the project, did you increase your ability to motivate and work around a common goal?	4.5	2.0
During the development of the project, did you feel that your ability to work independently improved?	4.1	2.5
During the development of the project, did you think your ability to formulate and manage projects improved?	4.1	2.6

central system. The results of the proposed CNN training were better than the results obtained from the compared CNN. This supports future work towards the optimization of the behavior of autonomous boat decisions, for example, by measuring the distance, size and relative speed of floating objects. We expect this experience to help practitioners in the process of retraining the CNN and in the application of this method to improve the image's recognition process.

Detection and recognition of floating objects in the sea is a theme of great importance in the fields of civil protection, environmental care, and applications for maritime navigation. In this study, we proposed retraining CNN that detect floating objects in real-time using the prototype of an autonomous navigation vessel, fed through a solar energy system. For the detection of floating objects, a neural network was trained in 9 categories which were compared with other existing methods, achieving superior levels of recognition than the proven methods.

3.4 Assessment

The competencies assessed in each project correspond to the tuning model for Latin America. The assessment model considered a matrix activity with learning results. Assurance of student learning was achieved through the compliance of the learning factors [91, 92]. It used a series of questions qualified by the 5-point Likert scale and seeks to compare the different variables between the projects developed during 2019 using the master class learning methodology with the execution of individual AI projects versus the AI project using the PBL methodology. The results are shown in Table 3.

To establish the effectiveness of the PBL method, a control group was established (35 students) to execute a null hypothesis of equality of means among the averages of the control group using the learning method of masterclasses and the course with PBL methodology (42 students). The statistical test was rejected when the average of the course with the PBL methodology was higher than that of the course used as a control group.

Both groups started the semester with an initial knowledge test and the accepted hypothesis test; the two groups had similar knowledge at the beginning of the semester.

4. Conclusions

Through PBL, engineering students developed (1) the design of the product, (2) the technical studies, (3) the software engineering (4) the prototype and (5) the functional tests of the product. This multidisciplinary work allowed students to quickly join the management of complex engineering projects.

The model proved to exceed the traditional model for large magnitude projects; most of the students complied with the due dates of the assigned tasks, demonstrating an appropriate level of work and commitment with the project. At the beginning, the students felt lost when facing a new work methodology; professor guidance secured their curiosity and interests to highlight their selected areas, providing support to other teams, and reaching the finish line as a large team.

PBL driving force might be copied in other complex projects for different study areas; this contributes to the development of personal skills, teamwork, leadership, autonomy, and personal initiative.

Finally, the university directives established an economic contribution to develop the active learning methodology in other engineering courses. The reuse of knowledge and techniques learned by students and teachers allows increasing the technological defiance for higher engineering courses, reducing the learning time in student teams.

The students' perceptions during the development of the course with the PBL techniques are opposed, they accept and reject the method; the analysis of the experiences will allow us to visualize the benefits and propose continuous improvement of the learning process.

Acknowledgments – This research was supported by CIES (Research Center for Higher Education) of the San Sebastián University (USS).

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