LAB University of Applied Sciences

AI for Educational Board Games

LAB University of Applied Sciences
Bachelor of Engineering, Information and Communications Technology
2024
Sergi Cortés Guerrero

Abstract

Author(s)	Publication type	Completion year
Cortés Guerrero, Sergi	Thesis, UAS	2024
	Number of pages 52	
Title of the thesis **AI for Educational Board Games**		
Degree, Field of Study Information and Communication Technology, Engineer		
Name, title and organisation of the client -		

Abstract

Cutting-edge artificial intelligence (AI) technologies are rapidly advancing and finding applications across multiple domains. Due to the surge of mobile applications, traditional educational board games, known for their multiple benefits, face the risk of being overshadowed. Rather than pitting traditional games against digital counterparts, this work explores how AI can strategically complement educational board games, ensuring their continued relevance and preventing complete digital substitution. The practical case demonstrates the enhancement of a straightforward educational board game by integrating said AI to offer a more comprehensive and enriching learning experience.

Keywords

Artificial Intelligence, Technological Adaptation, Games, Education, Computer Vision

Contents

1 Introduction

In the ever-evolving landscape of technological advancements, artificial intelligence (AI) stands at the forefront, revolutionizing various facets of our daily lives. As we witness the rapid progress of cutting-edge AI-related technologies with applications spanning multiple domains, such as natural language processing or image generation (World Economic Forum 2021.), exploring their potential impact on educational paradigms is imperative.

Amidst the rapid proliferation of technologies spreading throughout all aspects of our daily lives, a venerable educational tool faces the potential of being overshadowed—the traditional educational board game. Renowned for their effectiveness in reinforcing knowledge and encouraging interactive learning experiences, these timeless classics are at a crossroads in the digital age. (Lee & Raziff 2021.)

This work seeks to delve into a critical juncture where the traditional and the modern intersect. Rather than framing a dichotomy between classic games and their digital counterparts, the focus is on a strategic synergy. To ensure their continued relevance in the face of an ever-increasingly digitalized world, this work's overarching question is: How can AI be integrated into educational board games?

The significance of this inquiry lies in preserving the essence of time-honored educational tools and in harnessing AI's transformative potential to enhance learning experiences. By strategically merging AI with traditional games, the aim is to create a harmonious coexistence where the strengths of both approaches converge.

To unravel the potential of this integration, a specific practical case will be presented, demonstrating how a simple educational board game can be elevated by incorporating said technologies. It will serve as a testament to the current virtues of integrating AI.

2 Board Game in Education

2.1 Educational Games

Becker (2021) describes educational games as a specific category within serious games, a branch of games designed to entertain and fulfill broader objectives. This category encompasses various games, such as those aimed at improving health, effecting social change, serving as advertising tools (advergames), and engaging with political themes. Consequently, an educational game is categorized as a serious game specifically crafted to facilitate learning, as outlined in Table 1.

Allery describes an educational game as a learning instrument designed to engage students through competitive tasks regulated by specific rules. This definition emphasizes the dual purpose of educational games: to educate and engage, ensuring that learning is effective and enjoyable. (Allery 2014.)

Table 1. Comparison between Games, Serious Games, and Games for Learning (Becker 2021.)

	GAMES	SERIOUS GAMES	GAMES FOR LEARNING
BASIC DEFINITION	Includes both Serious Games and Games for Learning.	Games created for objectives beyond just entertainment, or that serve additional purposes.	Games crafted to achieve specific educational objectives.
PURPOSE	Can be for any.	Change in behavior, attitude, health, understanding, knowledge.	Normally connected with some educational goal.
PRIMARY DRIVER (WHY USED)	Can be either play or rewards.	To get the message of the game.	To learn something.
KEY QUESTION	Is it fun?	Is the message being received?	Is it effective?
FOCUS	Player Experience	Content / Message	Content / Message

BUSINESS MODEL	User Pays	Producer Pays	Varies

Furthermore, it's important to recognize that educational games extend beyond just board games. For instance, video games can also be effective learning tools if their focus is educational, as previously mentioned. (Pope 2021.)

2.2 Educational Board Games

Board games have traditionally enjoyed immense popularity in familiar settings, among groups of friends, and, in the case of educational games, also in scholarly use cases. They offer significant benefits, including cultural and educational value transmitted by many of them. Additionally, the interactions between participants, who may belong to different age groups and possess unique characteristics, make board games an excellent tool for strengthening social relationships and promoting teamwork. Furthermore, values such as respect, fellowship, or brotherhood are potentiated through these experiences. (Campoverde-Ordoñez & Espinoza-Freire 2019.)

They serve as valuable teaching mechanisms because students with different learning styles can collaborate effectively. They prepare players to react to unpredictable events, increasing the likelihood of problem-solving outside the classroom. Additionally, traditional teaching methodologies such as lectures and required readings are less effective than a learning process involving role-playing, simulations, team tasks, brainstorming, and interactive discussions. Games, the most ancient and time-honored approach to education, are played primarily to face adversity and develop the skills needed to overcome it. (Tasnim 2012.)

Also, the established benefits include students gaining experience in decision-making and collaboration as they navigate complex scenarios and uncertain conditions. Collaboration implies considering individual strengths in games where a player is supposed to play together with other players to achieve a common objective. However, it is essential to note that only some aspects of games are perfect; caveats include the possible oversimplification of the natural world and the very real chance that it might focus people on figuring out who made the biggest mistake rather than learning from these mistakes and perhaps losing a game. (Despeisse 2018.)

2.3 Examples of Educational Board Games

The following subsections will explore some games designed to enhance cognitive abilities and life skills, including but not limited to planning, decision-making, logical reasoning, and navigating through challenges, among others.

2.3.1 Kloo

Kloo (Figure 1) originated from the inventive mind of Andrew, an American game designer married to an Italian woman. Driven by the desire to teach his daughters new languages, he created this game when he observed their need for more enthusiasm for traditional language lectures. Andrew set out to design a game replicating the natural process of learning a first language. He found through experimentation that children and adults unconsciously learned between twenty and thirty new words in their target foreign language per game. (Fábrega n.d.)

Figure 1. KLOO Learn French 'Race to Paris' (Amazon 2011.)

2.3.2 Monopoly

A globally-renowned traditional board game designed for up to eight players, this real estate game involves buying and enhancing property pieces, aiming to accumulate the most wealth by the game's conclusion. Essentially, the game serves as a representation of capitalist principles. (Fábrega n.d.)

In an interview, Philip E. Orbanes, who wrote "Monopoly, Money, and You: How to Profit from the Game’s Secrets of Success", described how playing Monopoly (Figure 2) teaches important life skills. These skills encompass strategic planning for achieving objectives in games and real life, managing finances, diversifying investments, making decisions, negotiating, and coping with challenges and elements of chance. Additionally, the game promotes the development of mathematical abilities, aids children in understanding aspects of adult life, and allows them to compete equally with adults. (Jingles 2013.)

Figure 2. Children playing Monopoly (Kim 2021.)

2.3.3 Settlers of Catan

Another famous multiplayer game that emphasizes strategy is set on the fictional island of Catan. In this game, each player has a settlement and competes to become the dominant force in the region. Players must collect resources to build cities or roads, among other strategic actions, to achieve this goal. (Fábrega n.d.)

During gameplay, participants learn valuable skills, including resource management, as they decide where to allocate their limited resources. Negotiation skills are harnessed through reliance on others for resource trades. Environment analysis becomes crucial for success, as players must discern high-demand resources, understand how opponents have established their settlements, and identify resources that are no longer relevant—losing leverage in future negotiations if overlooked. (Fábrega n.d.)

2.3.4 Scrabble

A competitive board-and-tile game designed for two to four players involves creating words on a board using lettered tiles (Figure 3). The game commences with players drawing seven tiles from a pool, and they can exchange tiles after each turn. The frequency of use of the corresponding letters in English words determines the point values of the letter tiles. Consequently, higher frequency letters like 'a' yield fewer points than less common ones like 'z'. (Britannica, T. Editors of Encyclopaedia 2023.)

Research conducted by Khaira, Ritonga, and Halim demonstrates that playing this game can significantly enhance students' vocabulary compared to those who did not engage in it. The findings reveal an average increase of 50% in learning outcomes. (Khaira et al. 2021.)

Figure 3. Closeup Photo of Scrabble Game Board (Gimpel 2018.)

2.3.5 Chess

A timeless classic strategy game originating in India boasts over five hundred years of history. This game (Figure 4) actively stimulates brain growth and has been linked to increased IQ, as evidenced by a study involving four thousand students who improved their scores after just four months of chess instruction. (Fábrega n.d.)

Moreover, chess imparts many valuable skills, including cultivating focus and concentration. This stems from the necessity to concentrate entirely on the board, visualizing pieces, moves, and potential countermoves for compelling gameplay. Additionally, chess instills the importance of planning and foresight, encouraging players to think ahead of time. Logical thinking becomes a key component, as players must constantly evaluate potential outcomes of their moves and anticipate their opponent's responses. (Fábrega n.d.)

Figure 4. Chess match (Parzuchowski 2020.)

2.4 Contemporary Trends

Educational games offer invaluable learning benefits, but a recent trend has seen the substitution of traditional board games with digital versions. This shift is primarily driven by the rapid integration of new technologies and electronic devices in classrooms, exposing children to smartphones, tablets, video game consoles, and cutting-edge devices like virtual reality glasses. (Raja & Nagasubramani 2018.)

The rise in technology adoption has expanded educational opportunities but has concurrently caused a marked reduction in the usage of traditional board games (Lee & Raziff 2021). Despite the soaring popularity of digital offerings, educational and health professionals continue to raise alarms about the dangers linked to excessive technology use. Research, like that conducted by Alghamdi, points to detrimental effects on personal well-being, social interactions, and general health, including problems such as obesity, computer vision syndrome, and depression. (Alghamdi 2016.)

However, it is crucial to recognize that technology and board games need not be incompatible. There is an opportunity to merge both worlds' advantages and mitigate traditional media's decline. Artificial Intelligence (AI) plays a pivotal role in achieving this integration. Originally designed to bring human intelligence closer to machines, AI has evolved with technological advancements and the increased capacity for handling vast data sets. In the contemporary landscape, machines can tackle unprecedented challenges, such as autonomous driving, shape recognition, and the comprehension of arbitrary images. This collaborative approach can harness the strengths of technology while preserving the unique benefits of traditional board games. (Li et al. 2022.)

3 The Intersection of AI and Education

3.1 AI in Education

Artificial intelligence's integration into education began in the 1960s, spearheaded by the US Department of Defense initiatives focused on equipping computers with the capability to imitate basic human cognitive functions. The Defense Advanced Research Projects Agency (DARPA) laid essential foundations for automation and systems that enhance human abilities, such as expert and intelligent search systems. Over the years, AI has profoundly influenced various sectors, and its role in education has notably transformed schools and classrooms, significantly easing the workload of educators. (Tahiru 2021.)

AI technology has already been integrated into our daily lives, affecting not only how we live but also how we learn. Educational materials are now easily accessible through smart devices, marking a significant shift in how people approach learning. (Tahiru 2021.)

3.2 Early instances of AI integrations

Automation of Administrative Tasks: AI processes repetitive administrative tasks, saving educators valuable time grading exams and assessing homework. While technology exists for grading multiple-choice exams, challenges arise regarding essay-type questions, prompting ongoing research and development in employing AI for such tasks. For instance, AI can automate the admission processes for new students entering educational institutions. (Tahiru 2021.)

Innovative Content: AI applications are being developed to transform textbooks into efficient exam preparation tools, incorporating features like true or false questions. Prominent examples of these innovative content applications are Cram101 and JustTheFacts101, which utilize AI to enrich textbook material by offering chapter summaries, flashcards, and practice tests to improve understanding. Another significant innovation is the Netex Learning AI system, which facilitates the creation of digital curricula and educational content through online support programs with audio and video illustrations. (Tahiru 2021.)

Intelligent Tutoring System (ITS): Since the 1970s and 1980s, AI researchers have pursued the goal of self-tutoring, a concept originally developed by educational psychologist Benjamin Bloom. This concept has significantly evolved. A key illustration of this progress is the "Mike" Software from Carnegie Learning, which utilizes cognitive science and AI technologies to create a personalized student tutoring system. (Tahiru 2021.)

An ITS is a computer program that, with AI, can grasp the students' current knowledge level and develop the best learning approaches specifically curated for each student. (Syed et al. 2017.)

More in detail, it provides a tailored series of information, tasks, and assessments for every student. As a student tackles the material given, the system captures a wide range of data, including the items clicked by users, typed inputs, and task responses. This data undergoes an analysis to identify misconceptions and/or lack of knowledge in some areas. Then, the subsequent information, tasks, and quizzes are presented differently for each student, creating an individualized progression through the learning material. This interactive process continues in a loop until they have effectively learned. (Holmes & Tuomi 2022.)

3.3 State-of-the-Art AI Applications

The following subsections will explore some examples of famous AI tools to illustrate how AI is currently being applied to education in several ways and for different end-users; these end-users can be students, teachers, or even institutions. (Holmes & Tuomi 2022.)

3.3.1 Chatbots

The recent groundbreaking development of large language models, such as ChatGPT from Open AI, has allowed a never-before-seen level of support in response to a request from the student. These systems, among many other things, can provide entire essays, summarize information, or explain concepts (Figure 5) in seconds. (Gan et al. 2023.)

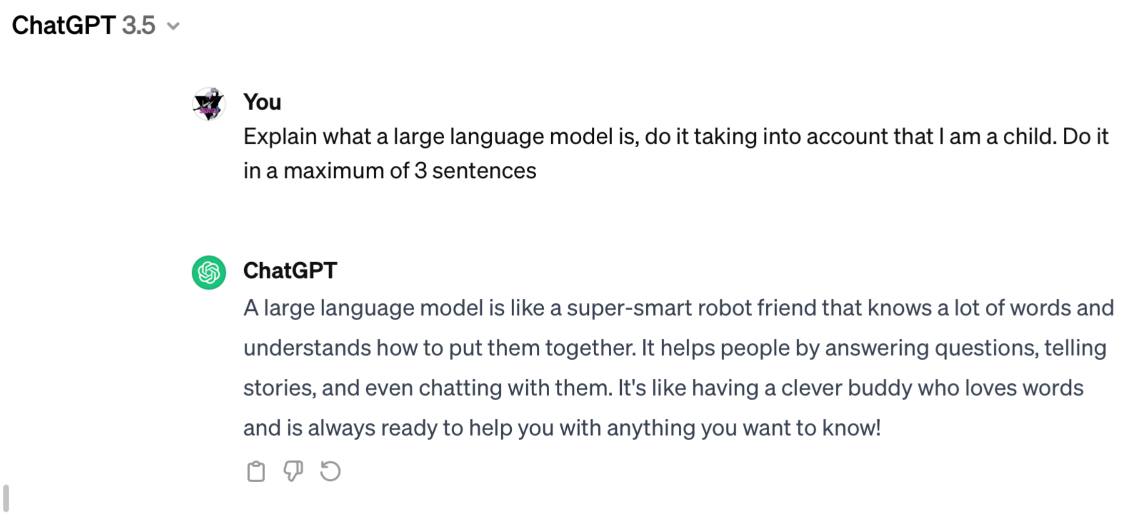


Figure 5. ChatGPT explaining what a LLM is

3.3.2 PhotoMath

PhotoMath is a convenient and intelligent mathematical tutor that is approachable to students and their parents. It is an IA application available for mobile devices; it takes advantage of the camera for reading mathematical problems; by pointing it towards the problem, it can provide a step-by-step solution. (Nguyen & Chen 2016.)

3.3.3 Grammarly

Grammarly (Figure 6) is a real-time application that can help non-native and native English speakers with grammar, writing, style, plagiarism, and tone. Many studies have highlighted its positive impact on English language proficiency and writing performance. Soegiyarto (2022) and Fitria (2021) found that the app significantly improved students' writing skills, with Fitria noting a substantial increase in test scores.

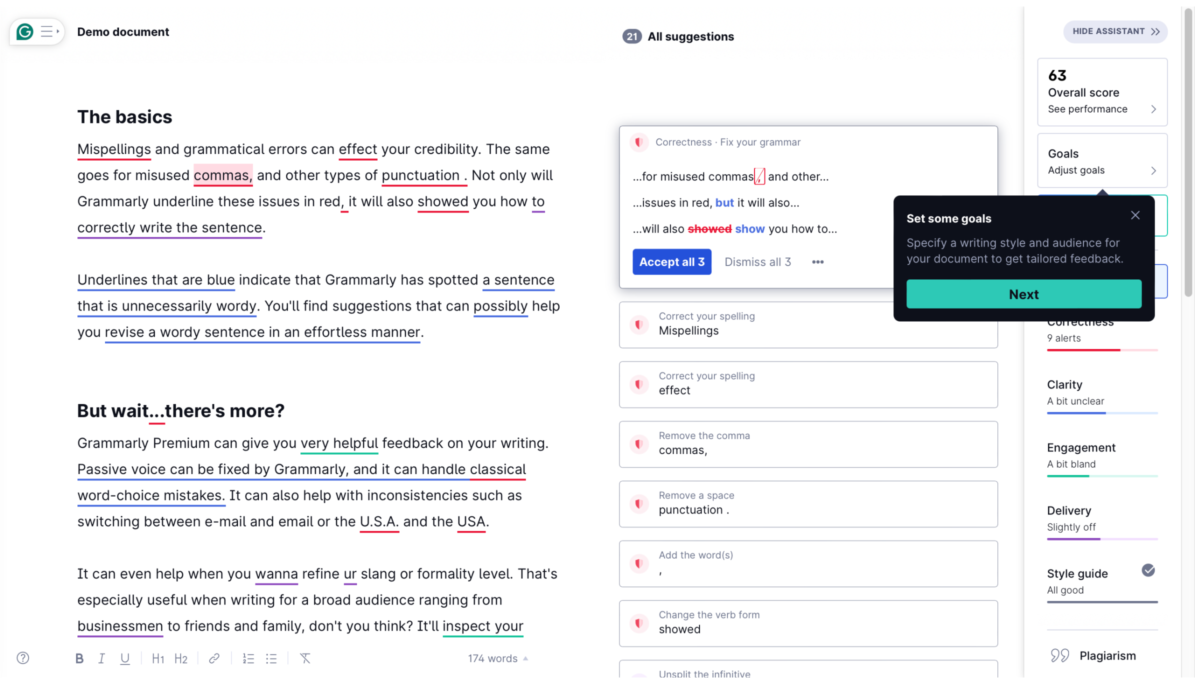


Figure 6. Grammarly Web-app

4 Artificial Intelligence (AI)

4.1 Overview

Before entangling what AI is, intelligence must be defined. Still, there has yet to be a widely accepted definition since philosophers, engineers, psychologists, and many other societal roles have their versions. In general, a thing is considered intelligent if it is adaptative and autonomous, meaning there is no need to provide instructions constantly, and it can change its behavior in front of environmental changes. (Linares 2022a.)

Due to the previous, AI lacks a single, widely accepted definition; Academic researchers emphasize its complexity, and EU regulations focus on market access. UNICEF defines AI as machine systems influencing environments based on human-defined objectives. At the same time, another possibility could be researching how a computer can do tasks that humans are more capable of solving now. (Holmes & Tuomi, 2022; Linares 2022a.)

There are two main approaches or so-called schools of AI (Holmes & Tuomi, 2022; Linares 2022a.):

- top-down, symbolic, or knowledge-based
- bottom-up, connectionist, or data-driven.

Top-down AI is based on the idea that first, a professional in the field defines the rules and logical principles; this is called expert knowledge. Then, once the expert knowledge is transferred, the AI can infer new concepts via deduction; these AIs are usually called expert systems. Still, one of its numerous limitations is the difficulty of surpassing the expert who gave the knowledge. Nowadays, it is called the old AI, which is still useful but is losing ground against the data-driven approach. However, unlike the other type, it allows for transparent system behavior, which means the reasons behind every decision are clear and can be understood. (Linares 2022a; Holmes & Tuomi, 2022.)

IBM's chess computer in 1997, Deep Blue, achieved a historic milestone by beating the reigning world champion, Garry Kasparov (Figure 7), showcasing the prowess of expert systems in AI. Deep Blue's strategy involved calculating future moves and evaluating chess positions with insights drawn from chess masters. This blending of computation and expert knowledge marked a turning point, demonstrating AI's capability in complex decision-making. (Fyhn 2019.)

Figure 7. World chess champion competing against Deep Blue (Mihalek 1996.)

Bottom-up AI has the opposite idea; it is based on simulating biology, meaning learning from observation or experience; instead of introducing the rules, the AI is given a large collection of examples from which it will infer them. It relies on the fundamental idea that a computer can optimize predictions by adjusting its behavior based on large datasets and a defined criterion for improvement, for example, finding the most probable word that follows a sentence. (Linares 2022a; Holmes & Tuomi 2022.)

Bottom-up AI has achieved notable success in various fields over the last decade. The reasons why it is currently on top are:

- exponential growth in available data
- reached enough computing power and storage
- development of complex learning models (Holmes & Tuomi, 2022; Linares 2022a.).

Exponential Growth in Available Data

The widespread adoption of digital devices and the rise of the Internet of Things (IoT) have resulted in an unprecedented surge in data collection. This abundance of information serves as the lifeblood of bottom-up AI systems, empowering them to learn and adapt at an accelerated pace. With each passing day, the reservoir of data expands exponentially, providing fertile ground for AI algorithms to glean insights and make informed decisions. (Linares 2022a.)

Attainment of Sufficient Computing Power and Storage

The evolution of hardware technology has played a pivotal role in propelling bottom-up AI to its current zenith. Advances in processing units, such as GPUs and TPUs, coupled with the emergence of cloud computing infrastructures, have equipped AI systems with the computational muscle necessary to tackle increasingly complex tasks. Moreover, the availability of affordable, high-capacity storage solutions ensures that vast datasets can be stored and accessed efficiently, fueling the continuous learning process of AI models. (Linares 2022a.)

Development of Complex Learning Models

The relentless pursuit of innovation within the field of artificial intelligence has yielded sophisticated learning architectures that underpin the success of bottom-up approaches. Researchers have devised intricate neural network architectures, such as convolutional neural networks (CNNs) and "you only look once" networks (YOLO) (Figure 8), capable of extracting intricate patterns and relationships from raw data. Additionally, breakthroughs in techniques like reinforcement learning and generative adversarial networks (GANs) have broadened the repertoire of AI systems, enabling them to exhibit increasingly nuanced behaviors and capabilities. (Linares 2022a.)

Figure 8. Person tracking with YOLO, a real-time object detection system

However, this kind of AI has some serious limitations that the other type did not have, such as privacy issues, algorithmic discrimination or bias, algorithmic opacity, lack of veracity due to synthetic generation of videos, audio, photos, and text, excessive carbon footprint, etcetera. (Linares 2022a.)

Apart from the two schools of AI, there is also a difference between generative AI and discriminative AI; generative AI, as the name implies, occurs when it can produce new data samples that are similar to the training data; an example is Stable Diffusion. In contrast, discriminative AI finds patterns in the data for a future never-seen input value to predict what it is, for instance, a detector of spam emails. (Linares 2022a.)

4.2 Machine Learning (ML)

ML is an area inside AI based on the bottom-up approach; this is the area of study dedicated to enabling computers to learn without being explicitly programmed to do so (Figure 9), in other words, without human intervention. It is nothing new or revolutionary; it uses well-known statistical and mathematical concepts. (Linares 2022b.)

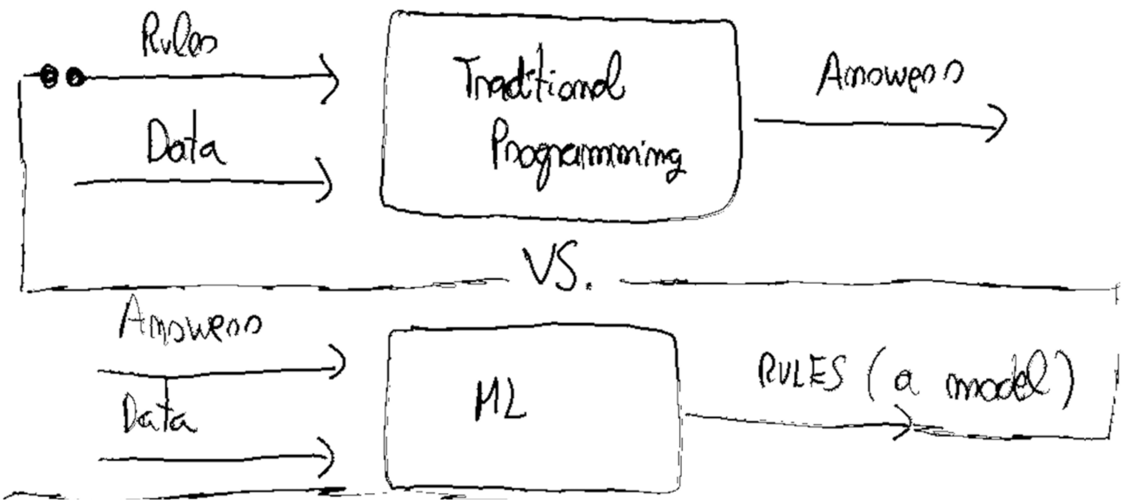


Figure 9. Traditional Programming VS ML

A so-called ML model is an algorithm generated on the provided data; it attempts to estimate a function *f(x)* from data (Formula 1); this function *f(x)* is the model, where *y* is the output and *x* is the input. The simplest ML model is a linear regression (Figure 10); from examples, it estimates a linear relationship between the input independent variable and the output. Once a model is obtained, it becomes possible to estimate outputs for new inputs; the accuracy of the results depends on how effectively the learning model can represent the probability distribution of the data, meaning that there will always be an error because it is a prediction not the actual answer. (Linares 2022b.)

$$y = f(x) \qquad (1)$$

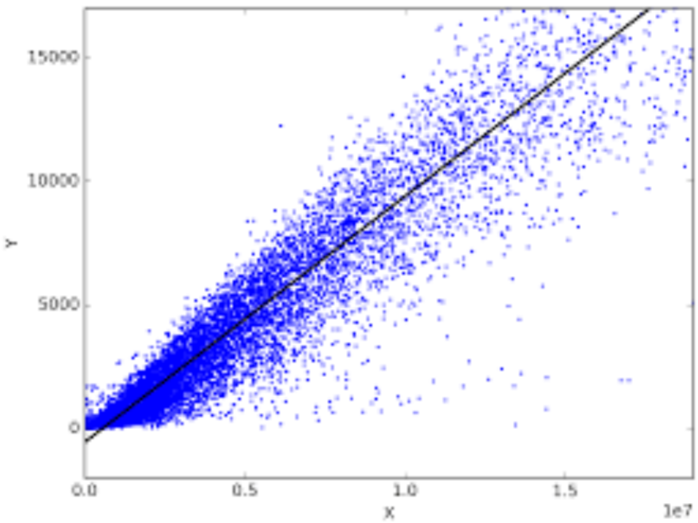


Figure 10. Example of linear regression (Linares 2022b.)

AI, in general, but especially ML, should only be used if there is no other analytical method available; the reason is that AI only gives us a prediction, and as such, it has a degree of error; it is not the perfect answer, it is a close-enough one that sometimes is useful. (Linares 2022b.)

However, ML should be applied in cases such as when

- the task is too hard or impossible to be programmed manually
- adaptability is required
- sufficient data is available
- facing large space search problems (Linares 2022b).

In summary, ML consists of a range of algorithms and methods designed to autonomously learn from provided data to find a general model capable of giving great results against data not seen before. This process is called knowledge induction. (Linares 2022b.)

There are several types of ML:

- supervised
- unsupervised
- reinforcement learning
- semi-supervised
- self-supervised (Linares 2022b).

Supervised learning is used when labeled data is provided, for instance, images of animals and the labels describing which animal is in the picture; this information can be used to make classifications or to solve a regression problem, which predicts a numerical value such as how much liters of gasoline a car is going to consume given his specs, whereas, in unsupervised learning, there are no labels attached to the data, the AI, in this case, aims, for example, to figure out hidden patterns and detect anomalies. (Linares 2022b.)

With reinforcement learning, the algorithm is rewarded or penalized depending on its behavior; if it helps it reach its objective, it is praised and encouraged to continue in that direction, and if not, it is punished (Figure 11). The actions taken at first are random, but after the training process, they will no longer be due to the previously explained reward-punishment approach. (Linares 2022b.)

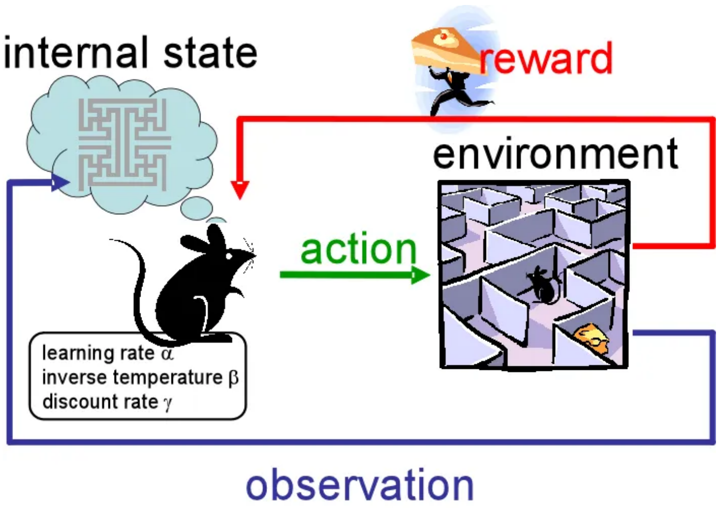


Figure 11. Reinforcement Learning (Das 2017.)

4.3 Supervised Learning

As stated before, its objective is to predict the label, also called the dependent variable, of a future set of features, also named attributes or independent variables, with a high level of accuracy, in other words, to generalize outputs in front of non-observed input data, thus successfully applying the knowledge acquired from the previously shown examples during the training phase. (Linares 2022b.)

If the prediction is a class or label, it is a classification; otherwise, if it is a numeric value, it is a regression. Classification can be divided into two types: binary and multi-class. Binary classification involves the AI choosing between two distinct labels, such as determining whether an image depicts a cat or a dog. In contrast, with multi-class classification, it must decide between more than two possibilities, such as when predicting a medical diagnosis. (Linares 2022b.)

In the training stage, relevant features are selected from the examples to build a model using any of the different ML algorithms. Meanwhile, in the prediction process, the identical set of pertinent features is extracted from the new input and then forwarded to the previously generated model to yield a prediction; Figure 12 depicts this concept. These two phases are not necessarily done on the same machine or platform. (Linares 2022b.)

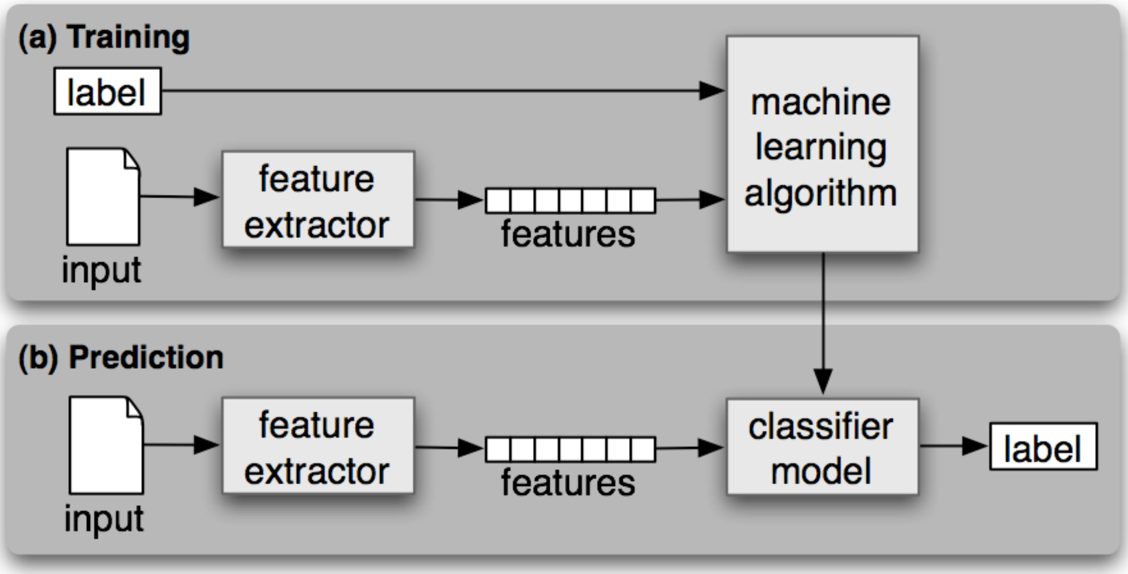


Figure 12. Supervised Classification (Bird et al. 2019.)

The feature extraction step is of paramount importance because obtaining good predictions depends solely on which features are chosen and which ML algorithm is applied; for instance, some algorithms have a well-known issue, “the curse of dimensionality”, which stands for: the more features it must consider the less accurate it will be. (Linares 2022b.)

For this reason, the first step is to perform exploratory data analysis or data cleaning. It involves investigating the data gathered by finding patterns, spotting anomalies, testing hypotheses, and summarizing their main characteristics, often employing data visualization methods. (Linares 2022b.)

4.4 Error Metrics

A fundamental question is How good the created model is; these metrics differ depending on the type of ML in use; in addition, it is unrecommended to calculate these metrics with the training data since the model could have memorized it, making it perform extremely poor in predicting results for new inputs, in other words, the model is not generalizing well, this problem is called overfitting. Therefore, a common practice is to use a test set, known as the hold-out technique; not all the available information is used for training the model; a small fraction is reserved for measuring its accuracy. (Linares 2022b.)

The hold-out technique allows for more statistically trustworthy metrics describing what would happen in front of new data; with it, overfitting and underfitting could be detected by comparing the metrics obtained from the training dataset and validation dataset, as shown in Figure 13; underfitting is the situation in which the model is too simple to explain the variance, meaning that it has not been able to learn effectively, it can be further improved. (Linares 2022b.)

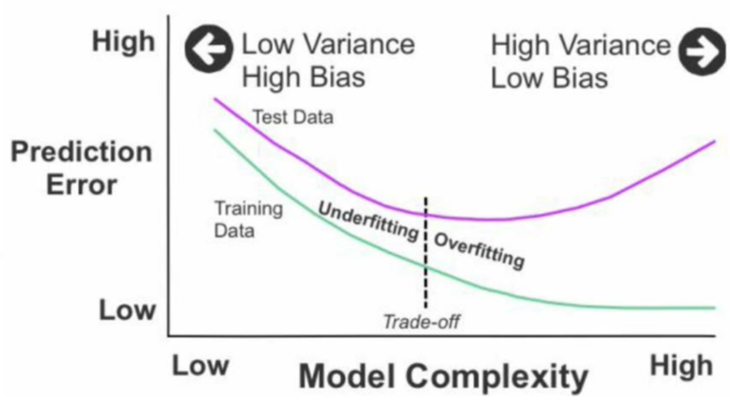


Figure 13. Comparing metrics (Linares 2022b)

To identify overfitting, the learning curve plots of training and validation must be compared; overfitting happens when a model's performance continually improves on the training dataset but deteriorates on the test or validation dataset. (Linares 2022b.)

To prevent overfitting, it can be done the following:

- obtain more data, preferably of higher quality
- early stopping
- cross-validation
- ensembling
- use of regularization (Linares 2022b).

Meanwhile, to prevent underfitting:

- change to another ML algorithm
- obtain more data, preferably of higher quality (Linares 2022b).

Early stopping is a mechanism based on halting the training process once the trade-off point is reached; the trade-off is when the model is not under-fitted or overfitted. Meanwhile, regularization is a technique that forces the ML algorithm to avoid learning small details by randomly deactivating some neurons, making the training process more demanding. In contrast, cross-validation gives better metrics and reliable models thanks to a systematic repetition of the hold-out technique; this approach entails splitting the data into several subsets or folds, assigning one fold as the validation set, and training the model on the other folds. This process is iterated, with each fold serving as the validation set. The results from each validation phase are then averaged to derive a final result. Lastly, ensembling combines multiple ML algorithms by mixing the predictions of several models. (Linares 2022b.)

4.5 Evaluation of Classification Algorithms

Classification techniques estimate the probability of belonging to a specific class; in other words, they not only deliver that a given image is of a dog but also its percentage of security, how sure the ML model is of its answer; this is called the degree of confidence. (Linares 2022c.)

In assessing a classification model's performance, two fundamental elements are considered: the actual outcome, often referred to as 'y', and the model's predicted outcome, commonly denoted as 'ŷ'. The model's prediction is categorized into four types: true positive, true negative, false positive, or false negative. (Linares 2022c.)

For example, consider a model designed to forecast whether an individual is likely to contract a specific illness. This model is developed using datasets that include individuals' information alongside predictive variables like age, gender, etc. Each individual's data is marked with an indicator specifying whether they are expected to contract the illness. An occurrence of the disease is indicated when the label is y = 1; conversely, if y = 0, the disease is not expected to occur. Considering this, Table 2 demonstrates the distinctions among the four prediction categories. (Linares 2022c.)

Table 2. Types of predictions – Confusion Matrix

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Predicted Outcome</td></tr>
<tr><td>ŷ = 1</td><td>ŷ = 0</td></tr>
<tr><td rowspan="2">Real outcome</td><td>y = 1</td><td>True Positive</td><td>False Negative</td></tr>
<tr><td>y = 0</td><td>False Positive</td><td>True Negative</td></tr>
</table>

Table 2 is also known as a confusion matrix, representing a tabular distribution of the four previously mentioned types; the correct predictions are in the diagonal, which is what must be maximized to increase the model's performance. (Linares 2022c.)

Once the confusion matrix is obtained, several useful metrics can be extracted; some of these are the following:

- accuracy
- error rate
- precision
- recall or sensitivity
- specificity
- F-measure (Linares 2022c).

Accuracy (Formula 2) is the fraction of predictions the model successfully predicted well out of all predictions, ranging between zero and one; these extremes represent always missing or never failing in a prediction. In addition, the complement of accuracy is the error rate (Formula 3). However, these metrics alone are untrustworthy because they may not tell the full story; for instance, if there are one hundred samples in the dataset from which ninety-five are of class “dog” and the rest “cat”, if the model always returns class “dog” it will have an accuracy of 95%; to solve this issue the other metrics come into play. (Linares 2022c.)

$$Accuracy = \frac{True\ positives + True\ negatives}{True\ positives + False\ positives + True\ negatives + False\ negatives} \quad (2)$$

$$Error\ Rate = 1 - Accuracy \quad (3)$$

Precision (Formula 4) is used to know the proportion of correct positive predictions, generally when it is critical to minimize the number of false positives; for example, in a spam detector, if the model has a great number of false positives, many emails that are not spam are classified as such, thus defeating the purpose of its use. (Linares 2022c.)

$$Precision = \frac{True\ positives}{True\ positives + False\ positives} \quad (4)$$

Like precision, sensitivity/recall (Formula 5) measures the proportion of actual positives correctly identified; this is done by dividing all the times that the model outputted positively, and it was correct by all the times that the value was positive. It is used in cases where truth detection is of utmost importance, in other words, when the number of false negatives needs to be minimized, such as when providing a medical diagnosis for cancer; in this case, if the metric is low, it will result in no cancer when there in fact is. (Linares 2022c.)

$$Sensitivity = \frac{True\ positives}{True\ positives + False\ negatives} \quad (5)$$

Specificity (Formula 6) aims to measure the proportion of actual negatives correctly identified, which is the symmetric metric of sensitivity; if the specificity score is low, there are many false positives. False positives are samples classified as positive when there were negative; this provokes, for example, that a spam detector is constantly identifying emails as spam when they were not. (Linares 2022c.)

$$Specificity = \frac{True\ negatives}{True\ negatives + False\ positives} \quad (6)$$

Lastly, F-measure, also known as F1 (Formula 7), is a metric that summarizes the previous ones by combining precision and recall into one number. Maintaining a balance between precision and recall is vital, as an imbalance—where the model exhibits high precision but low recall or the reverse—will lead to a lower F1 score. If both are high, the F1 score will be high. (Linares 2022c.)

$$F - measure = \frac{2 * precision * recall}{precision + recall} \quad (7)$$

4.6 Deep Learning (DL)

Deep learning based on neural networks (Figure 14) is the most cutting-edge ML technique of the moment, not the best for every use case due to, for instance, not being the most suitable in front of structured data, but when facing unstructured data is excellent, such as the case of images, videos, raw text and many more. (Linares 2022d.)

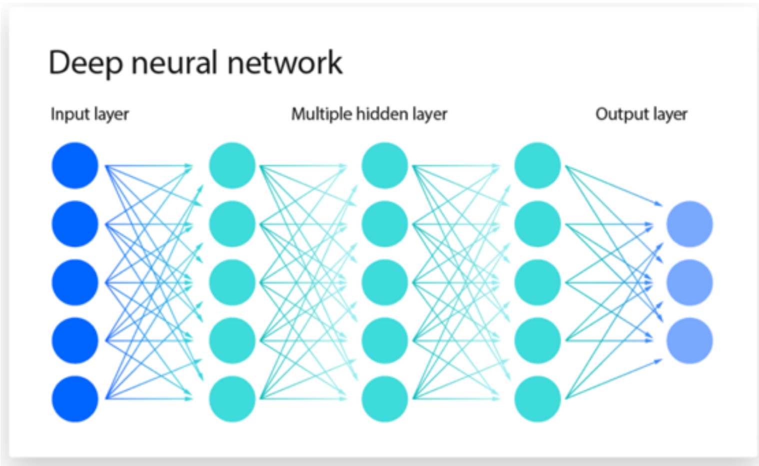


Figure 14. Example of Deep neural network (IBM 2024)

Deep learning is inside a field called representational learning; this field focuses on the idea of avoiding the feature engineering step; instead of manually selecting the features that the ML model must consider when deciding, an advanced ML technique automatically chooses them; the algorithm will find the best features and patterns even the ones hidden from us humans and will learn from them. (Linares 2022d.)

Deep learning represents the pinnacle of representational learning technologies. Designed to mimic the human brain's processing through multi-layered artificial neural networks, it enables computers to identify intricate patterns within data across various forms such as images, text, sounds, and beyond, facilitating precise predictions. (Linares 2022d; Amazon Web Services 2024.)

Deep Learning (DL) is widely used in numerous domains, such as facial recognition, speech recognition, natural language processing, and recommendation systems. In facial recognition, DL models analyze images to identify individuals accurately. In speech recognition, these algorithms can accurately interpret spoken words, accommodating variations in speech patterns, pitch, tone, language, and accent. For natural language processing, DL models are adept at extracting meaning and insights from textual data. In recommendation systems, DL algorithms analyze user behavior to generate tailored recommendations. (Amazon Web Services 2024.)

An artificial neuron is a small computing unit that can achieve intelligent behavior by connecting several of them in a network; it was introduced in 1943 by the name of threshold logic unit or linear threshold unit, but it was not refined until 1958 with the perceptron. (Linares 2022d.)

A neuron or single unit comprises a series of inputs with weights; the weights establish how important an input is; this includes a bias, an independent term that influences the output independently of the inputs, and an activation function that is applied to the sum of the bias and the products of each input with its corresponding weight (Formula 8); Figure 15 illustrates this concept. (Linares 2022d.)

$$Output = \sigma(b + \sum_{i=1}^{n} a_i * w_i) \qquad (8)$$

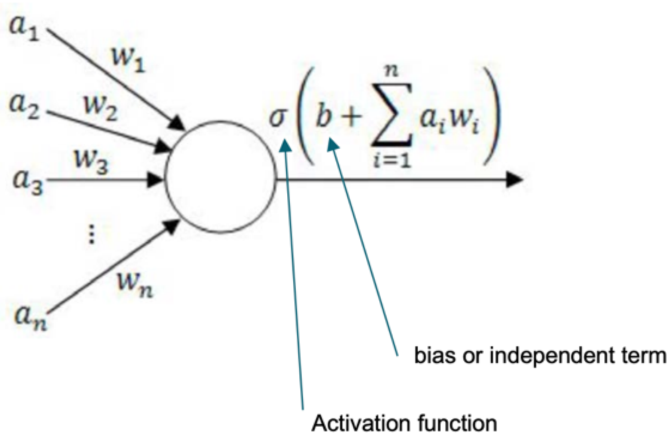


Figure 15. Artificial Neuron (Linares 2022d)

The activation function also receives the name of non-linearity; multiple functions can be used, but these functions must be derivable. One of the classical ones is the sigmoid function (Formula 9). (Linares 2022d.)

$$\sigma(z) = \frac{1}{1+e^{-z}} \qquad (9)$$

In 1989, George Cybenko formulated the universal approximation theorem, which asserts that any neural network containing at least one hidden layer (Figure 16) can approximate any continuous function, provided the inputs fall within a certain range. This implies that deep learning can perform any task, regardless of its complexity, with a specific degree of error. (Linares 2022d.)

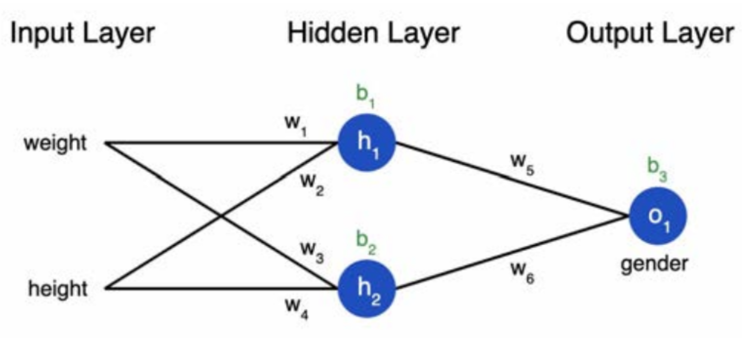


Figure 16. A Simple Neural Network (Linares 2022d)

Therefore, deep learning is based on neural networks; it needs more than 1 hidden layer to be considered as such. A neural network is a collection of artificial neurons interconnected through several layers. The first layer is always the input layer, the last is the output layer, and the rest are the hidden layers. (Linares 2022d.)

The neural networks are randomly initialized, and during the training process, the weights and biases of each neuron are tuned to minimize a cost function, also known as the loss function; this function describes the error produced calculated from how far the predictions made by the network are from the actual values. These weights and biases are tweaked using a famous algorithm called backpropagation. (Linares 2022d.)

Although the theory was developed during the 90s, it was not until recently that it exploded in popularity due to a key event in 2012: a contest for classifying images, ImageNet, was won by a colossal margin using a DL model, after that, the use of neural networks was not questioned again. (Linares 2022d.)

The final set of values of all weights and biases is the real knowledge extracted from the input dataset. To obtain them, a training process occurs in which an example is introduced.

A result is produced with a certain error, and the backpropagation algorithm sends backward gradients to update the weights and biases of the neurons; this process is repeated until the expected results are achieved. (Linares 2022d.)

In ML, the gradient is the loss function's slope or rate of change. Specifically, since the objective is to minimize this loss function, the gradient is used to adjust the weights and biases because it provides insights into the direction and extent of the most pronounced ascent or descent, guiding us in tuning the parameters to progress toward the minimum of the loss function thus the model is tweaked to get closer to the best possible outcome for the task, this concept can be seen in Figure 17. (Shonel n.d.)

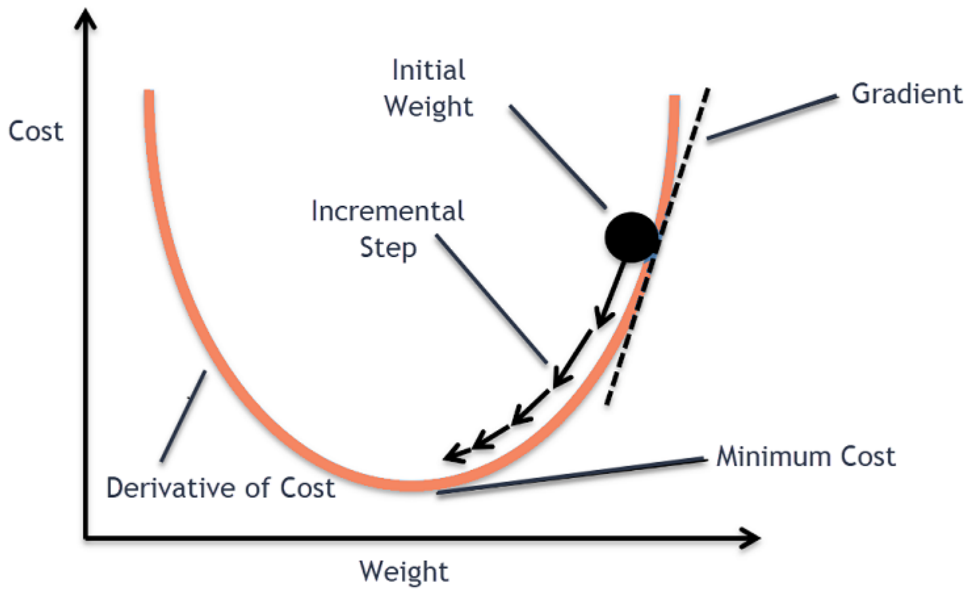


Figure 17. Gradient Descent (Crypto1 2024)

4.7 Convolutional Neural Networks (CNN)

Convolutional neural networks (CNNs), a subset of deep learning techniques, have revolutionized image processing and computer vision (Pinaya 2020; Bisong 2019). These networks are uniquely tailored to handle image data efficiently. They achieve this through a design that includes local connectivity, where neurons are linked to only a small, localized region of the previous layer, focusing on specific features like edges or textures. CNNs also feature spatial invariance, enabling them to recognize objects regardless of their position within an image. Additionally, their hierarchical organization allows them to process visual information in stages—from simple to complex features—mirroring how biological systems process visual inputs (Pinaya 2020). Unlike traditional fully connected networks, CNNs use convolutional layers that specifically target image-related tasks, setting them apart in versatility and effectiveness in fields like computer vision and natural language processing.

Inspired by the visual systems of living organisms, CNNs are adept at various applications due to these specialized capabilities. (Ketkar 2017; Ghosh 2019.)

A convolution is a common image processing technique that involves selecting an area, typically a square, around a pixel. The neighboring pixels are then considered to alter their value. For this purpose, a kernel or filter is used; it consists of weights that multiply with the pixel to achieve effects like blurring, sharpening, edge detection, and various others. The kernel is applied to the input image through a process called convolution, where the values in the kernel are applied to the respective pixel values of the image, and the resulting products are aggregated to produce a new pixel value for the resultant image, as shown in Figure 18. (Linares 2022e)

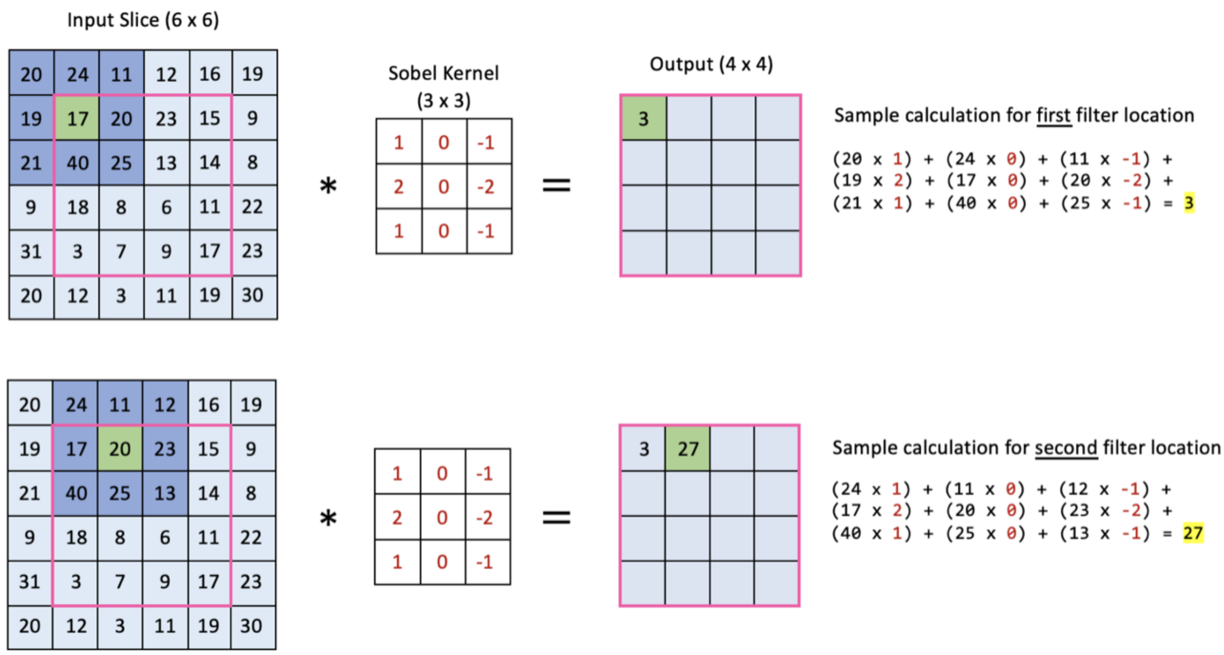


Figure 18. Example of a convolution operation (Kromydas n.d.)

One of the motivations behind the development of such neural network architecture was that when using a regular neural network, the number of trainable parameters depends on the image data, which is generally quite large, for instance, a minute image of 300x300 pixels with 3 channels for color representation has 270000 unique inputs making it unmanageable. Another reason is that fully connected layer neural networks tend to look at each pixel individually, so they will miss essential details and be prone to overfitting due to having one neuron for each pixel. (Kromydas n.d.; Linares 2022e.)

The CNN was designed to tackle these issues, being able to recognize from shapes to entire entities such as cars while having at the same time an independent number of parameters regarding the image size; all the parameters only depend on the filter size and the number of filters. Later, with the visual information gathered, the CNN passes this knowledge over to a regular neural network that can translate this visual information into a tangible output. (AI Tango 2024; Linares 2022e.)

In image processing, the filter weights are provided by the kind of operation carried out in the original image, whereas, in a convolution layer of a CNN, the weights will be learned based on its initial random values and the training process, finally automatically corresponding to a specific feature detection such as an edge or a mouth, therefore in practice, a filter is just one neuron. (Linares 2022e.)

The result of a convolution layer is a new representation of the image, a 3D volume whose depth depends on the number of filters applied (Figure 19). Each filter is moved across all the image pixels, obtaining an activation map. (Linares 2022e.)

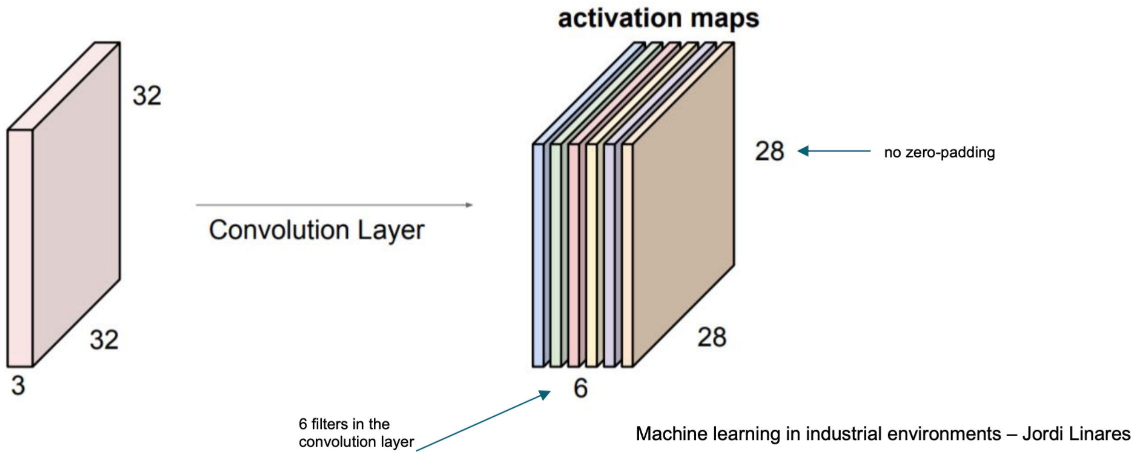


Figure 19. Result of a convolutional layer (Linares 2022e)

During the training process, the different layers of a CNN learn a hierarchical representation of the features of the image, meaning that the first layers recognize simple, low-level concepts like edges. In contrast, the last ones recognize high-level concepts thanks to the previous layers' efforts, allowing them to differentiate wheels, mouths, etc. (Linares 2022e.)

Apart from the convolutional layers, there is also another kind, the max pooling layer, whose objective is to reduce the size of the volumes produced by the convolutional layers to keep the computational cost under control. The final depth does not change; thus, the CNN keeps paying attention to the same number of features, but it makes the activation maps smaller by selecting maximums. (Linares 2022e.)

4.8 Data Augmentation

Training a good, performant ML model requires a large dataset; this is even more important when discussing a DL model like a CNN. Therefore, there is a common way to generate more data samples artificially; this mechanism is called data augmentation. (Linares 2022e.)

Data augmentation when working with images consists of performing subtle transformations or random changes to each image to get more images to train with (Figure 20); these new images are labeled as the original ones. It drastically increases the metrics in small datasets. (Linares 2022e.)

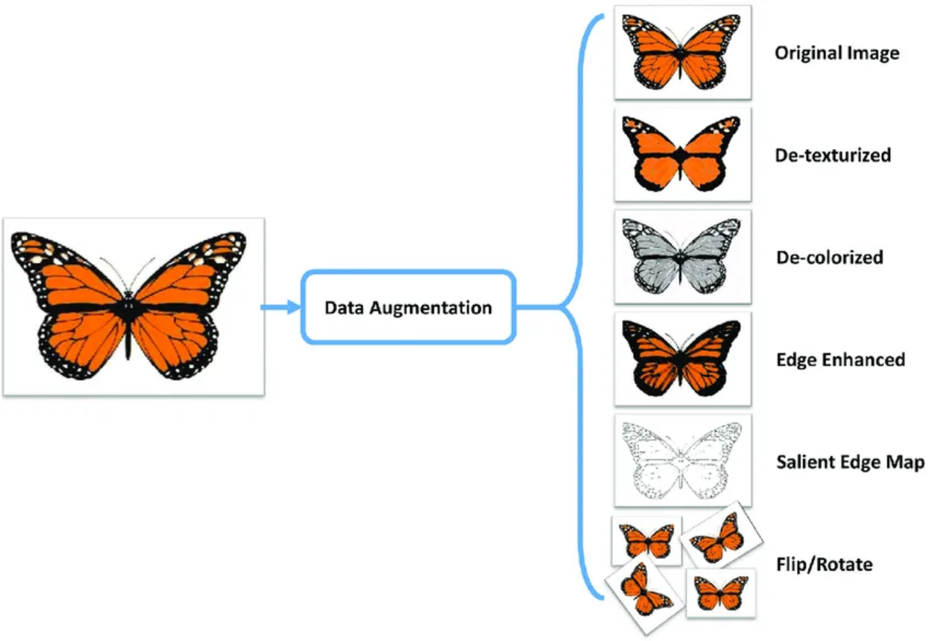


Figure 20. Example of augmentation (Kumar 2019)

Each pre-processing technique has unique benefits and disadvantages, for instance in the case of merging all color channels into one, it will result in a black-and-white image that, in turn, will make the model faster since it has less information to revise and insensitive to the subject color, but it can only be used when the color is irrelevant. (Nelson 2020.)

4.9 Advantages of a Fully Localized AI

Integrating AI has traditionally relied on server-based computing to handle complex processing tasks. However, the evolution of technology now allows for fully localized versions of these AIs, eliminating the need for constant server communication. This shift towards a local implementation offers numerous advantages, including improved accessibility, enhanced privacy, security, and greater educational value. (Lampou 2023.)

Enhanced Accessibility and Reliability

One of the most significant benefits of a fully localized AI is its accessibility. Without an active internet connection to a server, the product can be deployed anywhere, at any time, making it an invaluable tool for learning in environments where internet access is unreliable or unavailable. This feature is particularly beneficial for educational settings in remote or underserved areas, ensuring that geographical constraints do not limit learning opportunities. (Bayeck 2020.)

Moreover, the reliance on local processing eliminates latency issues commonly associated with server-based applications. Users experience seamless interactions with the product, with instant feedback and no delays, leading to a more engaging and enjoyable learning experience. (Bayeck 2020.)

Privacy and Security

By processing data locally on the device, fully localized AI offers enhanced privacy and security for users. In an era where data privacy concerns are paramount, local processing means sensitive information, such as personal data or educational progress, is not transmitted over the internet or stored on external servers. This significantly reduces the risk of data breaches and unauthorized access, offering peace of mind to students and educators alike. (Papadimitriou et al. 2019.)

Furthermore, local processing complies with stringent data protection regulations, making it easier for educational institutions to adopt these tools without navigating the complex legal landscape of data privacy laws. (Papadimitriou et al. 2019.)

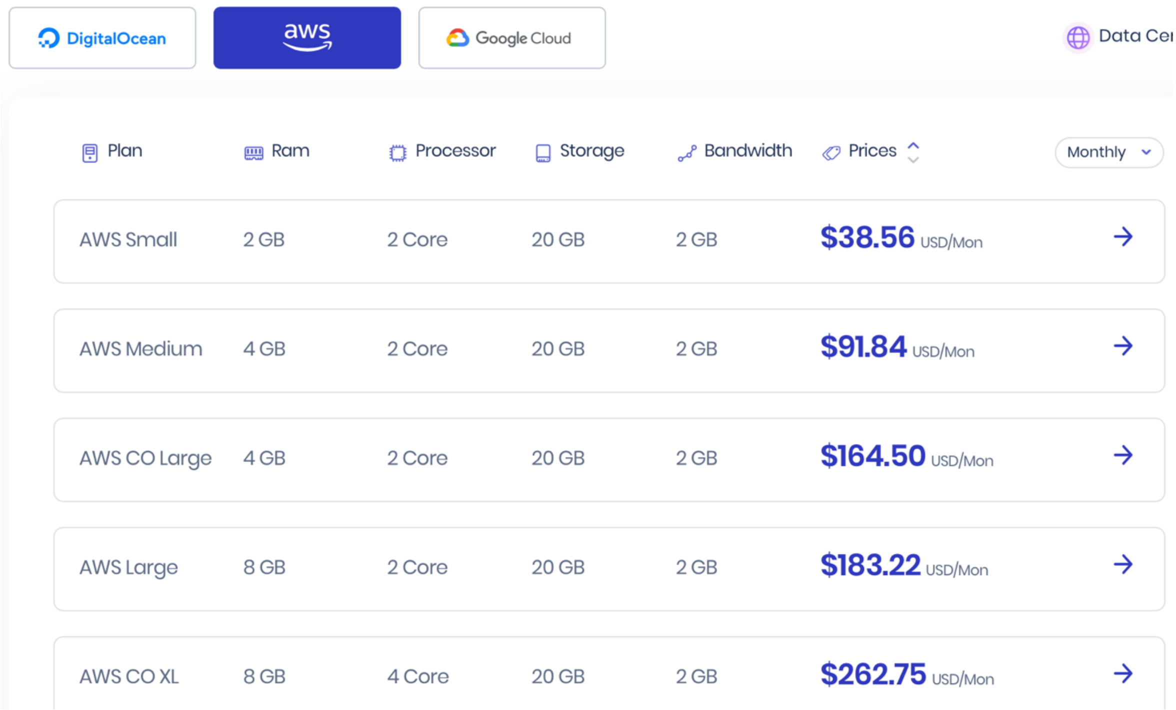
Educational Value and Customization

A fully localized approach allows for the customization of the educational content to match the individual or group's specific needs and learning pace. Unlike server-based systems, which may offer generic responses or content, localized AI can adapt dynamically to the users' progress, providing personalized challenges and feedback tailored to their unique learning journey. (Imani & Mulyanto 2023.)

This adaptability enhances the product's educational value, as it can adjust the difficulty level in real-time, introduce new words or concepts based on the student's proficiency, and even integrate culturally relevant content that makes learning more relatable and effective. (Imani & Mulyanto 2023.)

Cost-Effectiveness and Sustainability

Operating an AI-enhanced educational board game locally eliminates the need for continuous server use, which can be cost-prohibitive for developers and educational institutions (Figure 37). By reducing the reliance on cloud computing resources, the overall operational costs of maintaining and scaling the game are significantly lowered. This makes it more economically viable to provide these educational tools to a wider audience, including schools and communities with limited funding. (Price & Moore 2008.)



Plan	Ram	Processor	Storage	Bandwidth	Prices
AWS Small	2 GB	2 Core	20 GB	2 GB	$38.56 USD/Mon
AWS Medium	4 GB	2 Core	20 GB	2 GB	$91.84 USD/Mon
AWS CO Large	4 GB	2 Core	20 GB	2 GB	$164.50 USD/Mon
AWS Large	8 GB	2 Core	20 GB	2 GB	$183.22 USD/Mon
AWS CO XL	8 GB	4 Core	20 GB	2 GB	$262.75 USD/Mon

Figure 37. Pricing plans AWS

Moreover, local processing is more energy-efficient, contributing to environmental sustainability. Data centers powering cloud computing consume vast amounts of electricity and contribute significantly to carbon emissions. By minimizing the use of these resources, fully localized products present a more sustainable option for technology-enhanced learning. (Price & Moore 2008.)

5 Computer Vision (CV)

5.1 Overview

CV is fundamentally concerned with endowing computers with the ability to comprehend and interpret visual data from images and videos (Pandey 2023; Deshmukh 2021). This multidimensional domain encompasses an array of tasks, including but not limited to image classification, object detection and recognition, and semantic segmentation, each of which contributes to the holistic understanding of visual content. (Pandey 2023.)

The significance of computer vision is underscored by its wide-ranging applications across various industries, which include video surveillance, biometrics, automotive, medicine, and many more. For example, in video surveillance, computer vision algorithms facilitate detecting anomalies and identifying objects or individuals of interest, enhancing security measures. (Pulli 2012.)

Furthermore, computer vision is not considered AI in the strictest sense. While computer vision is closely related to AI (Figure 21), it is more focused on enabling computers to interpret and understand the visual world by analyzing images and videos to extract information. While AI technology can enhance computer vision to improve its capabilities, such as when using CNNs, they are distinct fields with different focuses and applications. (Inuwa 2023.)

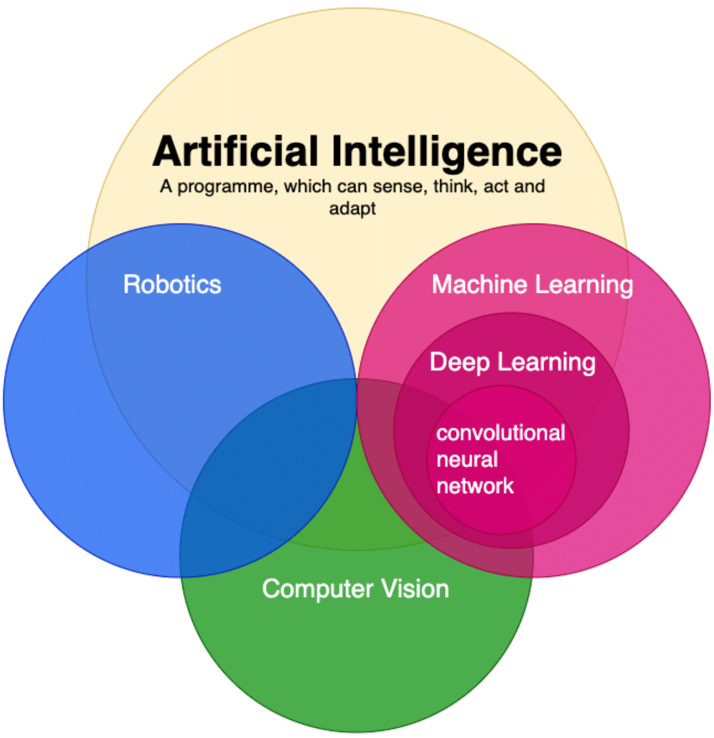


Figure 21. Relation between Robotics, AI, CV, and DL (Chandaliya 2020)

5.2 OpenCV

OpenCV, an acronym for Open Source Computer Vision Library, is the world's largest library dedicated to computer vision. It is tailored for computer vision and machine learning projects by offering a unified platform for various vision-based tasks, facilitating the integration of machine perception into commercial products. (Cervara 2020; OpenCV Team 2024.)

As referenced in Figure 22, the library contains more than 2500 optimized algorithms that span traditional and contemporary computer vision and machine learning techniques. These algorithms support an extensive array of capabilities, such as detecting and recognizing faces, identifying objects, classifying human actions in videos, tracking camera movements, modeling 3D objects, stitching images, searching for similarities in image databases, removing red-eye, tracking eye movements, recognizing scenes, and placing markers in augmented reality environments. (OpenCV Team 2024.)

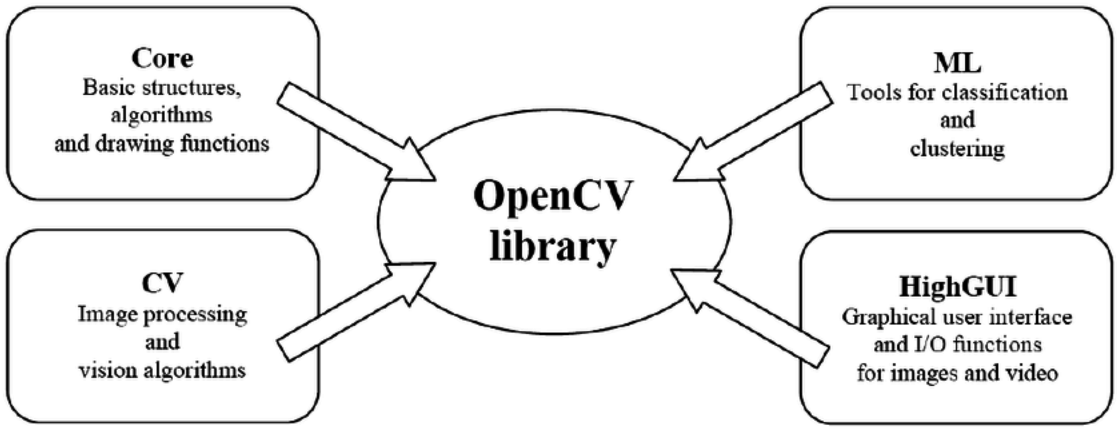


Figure 22. The basic structure of the OpenCV library (Kozlowski & Królak 2009)

OpenCV enjoys a vast user community of over 47 thousand people, with estimated downloads exceeding 18 million. It is extensively employed by companies, research groups, and governmental bodies worldwide. Notable users include Google, Yahoo, Microsoft, Intel, IBM, Sony, Honda, and Toyota, as well as startups like Applied Minds, VideoSurf, and Zeitera. (OpenCV Team 2024.)

The library is compatible with several programming languages, such as C++, Python, Java, and MATLAB, and it supports different operating systems, including Windows, Linux, Android, and macOS. OpenCV is primarily written in C++. (OpenCV Team 2024.)

5.3 Common Image Processing Techniques

One of the foundational aspects of CV is image processing, a set of techniques for manipulating and analyzing images to extract meaningful information, thus empowering machines to interpret and understand visual data. This collection of methods involves using algorithms to manipulate images, either to improve the quality of an existing image or to extract vital information from it. (Pain 2024; Kundu 2023.)

In image processing, there are several techniques commonly used, including the following:

- filtering and convolution
- histogram equalization
- edge detection
- image transformation and conversion
- feature detection and extraction
- image segmentation
- object detection and recognition (Pandey 2023).

Filtering and convolution

Convolution is employed to apply filtering techniques like blurring, sharpening, and noise reduction to images. It entails moving a filter or kernel across an image and executing mathematical computations on individual pixels. This method achieves anti-aliasing, edge detection, and texture elimination enhancements. (Pandey 2023.)

Histogram Equalization

Histogram equalization distorts the distribution of the pixel intensity values in the image to give a better contrast of the image. Extending the histogram uses the image's full dynamic range and improves the clarity and detail perception of the output image. This becomes very useful if there is poor light or the contrast is not high, although improving image quality is hard to accomplish. (Pandey 2023.)

Image Transformation and Conversion

Image transformation entails transforming the geometric properties of images for certain goals. Most of the changes made involve translation, rotation, scaling, and displacement, which are all parts of the transformations that assist in operations like image alignment, registration, and perspective correction. Image transformation could then be used to effect changes in the orientation, size, and/or spatial arrangements that could be useful in analyzing and interpreting the image in the subsequent processes. (Pandey 2023.)

Grayscale conversion and thresholding are fundamental techniques often employed. Grayscaling is transforming a color image into a grayscale version, where each pixel is depicted by a single intensity value that spans from black to white. This simplification retains essential image information while reducing computational complexity. Thresholding, on the other hand, involves segmenting an image based on a specified intensity threshold. Pixels with intensity values above the threshold are assigned one value, while those below it are assigned another, effectively partitioning the image into foreground and background regions. These techniques are crucial in various image processing tasks, including feature extraction, object detection, and image segmentation. (Pandey 2023.)

Edge detection

The edge detection algorithm seeks to identify significant transition boundaries within an image—namely, abrupt changes in brightness like edges, curves, or the outlines of objects. It plays a pivotal role in numerous applications, such as detecting objects, analyzing shapes, and extracting features. Prominent algorithms used for this purpose include the Canny edge detector (Figure 23) and the Sobel operator. (Pandey 2023.)

Figure 23. Canny Edge detection applied (Sahir 2019)

Feature detection and extraction

These algorithms are engineered to detect distinct visual patterns or structures in images, such as corners, edges, patches, or textures. Once these elements are identified, the algorithms employ numerical techniques, like histograms of oriented gradients (HOG), to extract and describe patterns. The detection and extraction of these features are essential for numerous applications, including object recognition, image fusion, and image localization. (Pandey 2023.)

Furthermore, contour detection is a crucial technique frequently employed in computer vision tasks facilitated by libraries like OpenCV. Contours are essentially the outlines or boundaries of objects present within an image. OpenCV provides several algorithms for contour detection, such as the popular "findContours" function (Figure 24), which locates and extracts these outlines. (Pandey 2023.)

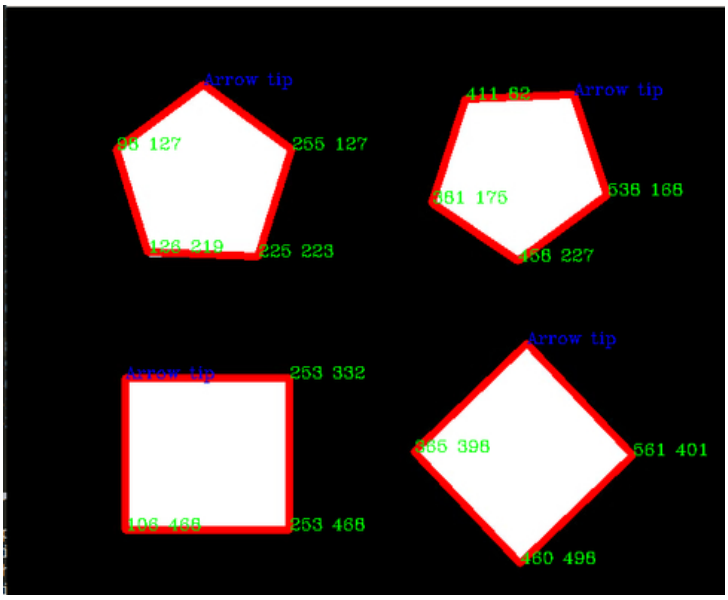


Figure 24. Finding Coordinates of Contours (GeeksforGeeks 2023)

Image Segmentation

Image segmentation is a partition of the image into several regions or sets, disjoint from each other, where each partition plays the attribute of the pixels in the image. In other words, it's splitting an object from the background or splitting an image into meaningfully grouped sections. Applying these techniques is a crucial initial step in various computer vision applications, including object detection, image annotation, and semantic understanding, due to the contribution to more accurate analysis and interpretation of visual data. (Pandey 2023.)

Object Detection and Recognition

Object detection and recognition entail identifying and classifying specific object patterns within an image or scene. This process typically necessitates training machine learning models using carefully curated datasets, which help the models learn the visual characteristics of the objects. Innovations in CNNs (Convolutional Neural Networks) and deep learning architectures have significantly advanced these tasks, enhancing the accuracy and robustness of object recognition across various fields. Some of the most critical applications of these technologies include autonomous driving, surveillance systems, and facial recognition, all of which have seen notable improvements in efficiency and precision due to these technological advancements. (Pandey 2023.)

6 Case: AI-Enhanced Intelect game

6.1 Introduction

Intelect (Figure 25) is an educational board game that exercises the mind while being entertaining, and its main objective is to improve vocabulary and mental agility. Intelect is a Scrabble-like game with a unique peculiarity. It is focused on learning new Spanish words; thus, the different quantities of word tiles are optimized to have a higher chance of drawing the most common characters, such as ‘a’ and ‘n’. Therefore, it is understandable that the game is only available in that language.

Figure 25. Intelect Deluxe (Falomir 2011)

More in detail, Intelect is a crossword game where players rely on both chances, as they draw letter tiles, and their linguistic skills to compose words strategically and accumulate the highest score. The objective is to amass points throughout the game, with the ultimate victor being the player who achieves the highest score when the game concludes.

6.2 Integration of AI

To enhance the educational and interactive aspects of Intelect, AI can be seamlessly integrated into the game experience. There are many possible ways to achieve this; in this practical case, it involves combining the cross-word game with a mobile application that utilizes AI capabilities.

For a clearer understanding of the potential contributions of AI to the educational board game experience, consider the following: In this integration, players will use a mobile app designed to capture the words formed by the letter tiles on the game board through a photo, and subsequently, validate these words against the Spanish language dictionary.

Therefore, the AI-driven application offers several functionalities, including:

- **Word Recognition**: The AI can accurately recognize and identify words formed by players on the physical game board, ensuring a seamless transition between the traditional and technological aspects of the game.
- **Dictionary Validation**: Once words are recognized, they will be validated against an extensive Spanish language dictionary, ensuring that only valid words are accepted, contributing to the educational value of the game.
- **Scoring Automation**: The app can automate the scoring process, calculating the points for each word based on the game's rules. This speeds up the gameplay and eliminates human error in scoring.
- **Game Progress Tracking**: The application can keep track of the game's overall progress, maintaining a record of each player's scores and moves. This feature allows for a more dynamic and interactive gaming experience.

By integrating AI in this manner, the objective is to complement the traditional board game format with the advantages of modern technology. This integration does not aim to replace the traditional format but rather to create a synergy between traditional gameplay and the benefits offered by AI and mobile technology. The result is a novel and enriched form of interaction that combines the familiarity of the traditional game with the advancements and convenience afforded by AI and mobile applications.

6.3 About the Technologies Used

In the modern landscape of technology-driven innovation, utilizing cutting-edge tools and platforms is paramount for achieving success in various domains. In this practical case, a convergence of powerful technologies has been harnessed to accomplish diverse objectives efficiently and effectively. The key technologies employed were the following:

- unity 3D
- google colaboratory
- tensorflow
- keras
- opencv.

Unity 3D

Unity is an integrated development environment and game engine designed to create interactive media, primarily video games. It manages various elements, including graphics, audio, physics, interactions, and networking. Known for its rapid prototyping abilities, Unity supports multiple publishing platforms, from smartphones to game consoles. (Haas 2014.)

It is also a powerful and versatile platform, extending its capabilities beyond gaming into various non-gaming applications; for instance, architects utilize Unity to create immersive 3D simulations for building visualization, helping clients make informed decisions and reducing costs. The automotive industry benefits from Unity in designing and prototyping vehicles, allowing engineers and designers to test materials and driving conditions. Medical professionals use it for risk-free virtual training in healthcare, improving patient outcomes. The education sector is experiencing a revolution through augmented reality and virtual reality applications, enhancing student learning experiences. (Bleeding Edge Studio 2023.)

Google Colaboratory

Google Colaboratory (Figure 26), commonly called Colab, is a cloud-based platform built on the foundation of Jupyter Notebook, facilitating the implementation of machine learning and deep learning techniques. It offers complimentary access to Graphical Processing Units (GPUs), essential for effectively applying deep learning principles. (Gujjar & Kumar 2021.)

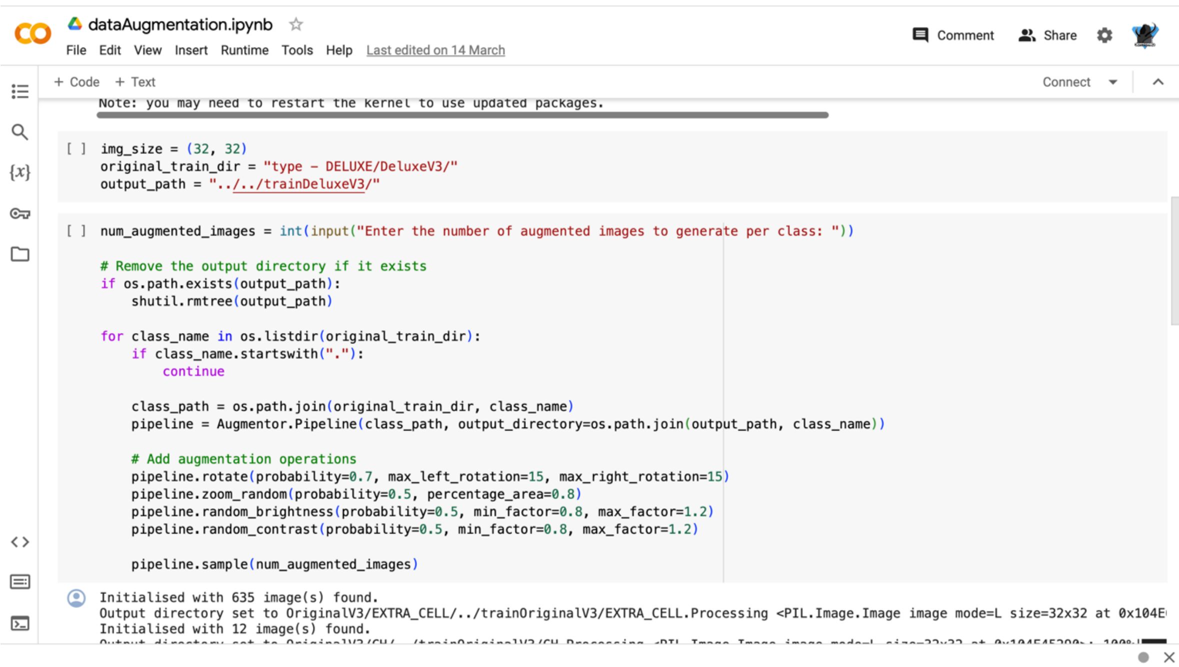


Figure 26. Data Augmentation Colab

Tensorflow

TensorFlow is a dedicated numerical computation library specifically crafted for deep learning activities. It is widely favored among deep learning researchers and professionals in various industries for creating and refining deep learning models and architectures. Additionally, TensorFlow is commonly used to deploy trained models to production servers and integrate them into software products. (Bisong 2019.)

Keras

Keras is an advanced Python library designed for deep learning and simplifying the building and training of neural networks. It is compatible with TensorFlow, Theano, and CNTK and offers a sequential and functional API for creating models. Keras abstracts away the complexities of these underlying frameworks, allowing developers to focus on the key concepts of deep learning. (Manaswi 2018.)

6.4 From a Picture to Word Validation

The process begins with a photo of the game board, where the square with the largest area representing the game board is identified using traditional computer vision techniques. Once the board's edges are detected, the perspective is reversed to eliminate the original photo's perspective, leaving it as if taken perpendicular to the board. Subsequently, the focus shifts to the game board area where players' tiles are located. This area is a square composed of 225 squares (15x15).

From the image of the game area, a strategy is chosen to crop the game area, obtaining 225 smaller images corresponding to each square. Once these images of each square are separated, a CNN is employed to recognize each letter of the game.

A dataset was created to achieve this, with images of each tile containing the game's letters. Using data augmentation techniques, numerous images of each letter are generated by altering parameters such as orientation, brightness, and contrast. This dataset is utilized to train the CNN. In this case, a simple vanilla CNN is employed to reduce resources and time during the prediction stage. Once the neural network is trained, the obtained model is used in the application to predict which letter appears in each image. Figure 27 illustrates this complex process in detail.

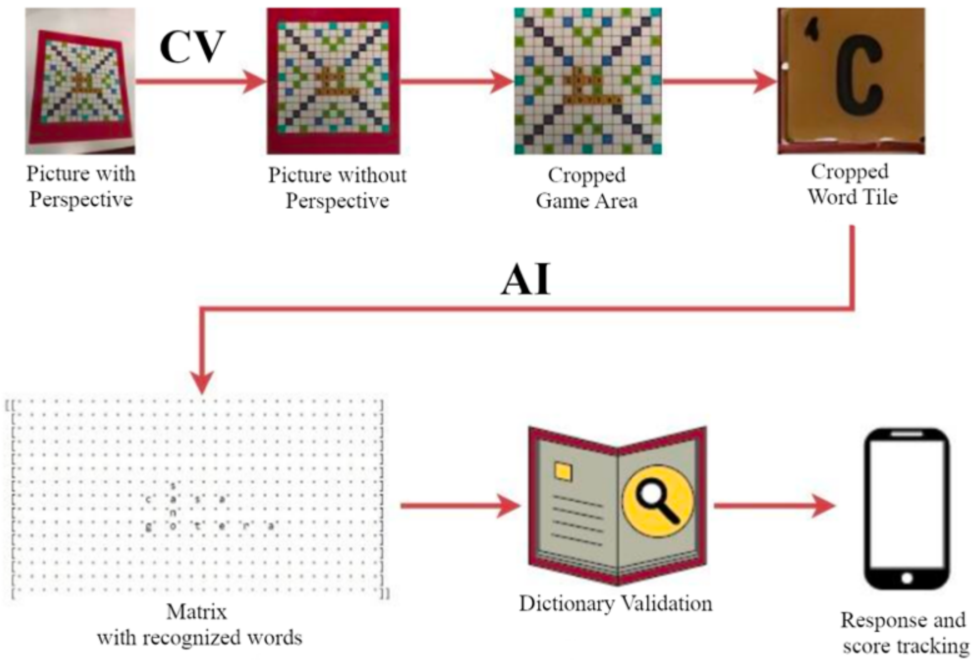


Figure 27. Game Process Diagram

6.5 Obtaining the Cropped Game Area

More deeply, the process involves computer vision techniques to obtain the cropped game area, specifically through the OpenCV library. Here is a step-by-step breakdown of the procedure:

- First, an image is captured.
- Secondly, a pre-processing step is performed to facilitate the identification of contours.
- Thirdly, all contours are detected.
- Next, the largest contour is selected, assuming it must be the game board.
- In the last stage, the perspective is removed using the previously gathered information and the inner game area is extracted using a simple crop since the game board dimensions are well-known.

The application continuously captures images from the device camera and resizes them for further processing. Each image undergoes a series of pre-processing steps: converting to grayscale, applying a light blur, and using the Canny edge detection method. These steps simplify the subsequent operations, reduce noise, and highlight important edges repectively.

A threshold is performed to enhance the accuracy of contour identification. Dilation and erosion operations are applied to refine the edges and address potential noise. These operations improve the quality of edge detection, although they are not strictly necessary.

The program then identifies and saves all contours in the image using an OpenCV function called "findContours". The largest contour is filtered and identified as the game board from the obtained contours. Additional checks, such as area filtering, ensure the contour represents a rectangle.

Once the largest rectangular contour is identified, a perspective transformation is applied using the corner points of this contour. To improve the accuracy of the cropped game area, 20 pixels are removed from each side to avoid artifacts. Figure 28 shows the previous process applied for creating a document scanner.

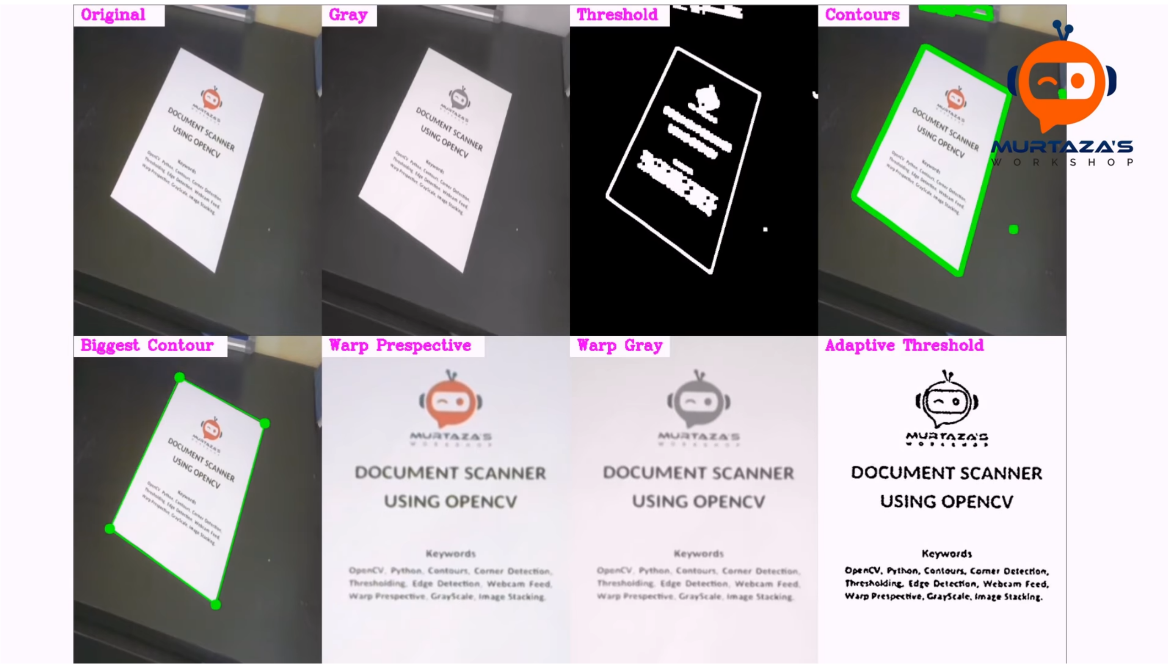


Figure 28. Document Scanner using OpenCV (Murtaza's Workshop 2020)

6.6 From Cropped Word Tile to Recognized Word

The workflow of the application is as follows: After obtaining the image of the board without perspective and cropping each word tile, the model provided by an AI is used to predict which letters the player has incorporated into the new move. The board is converted into a 15x15 matrix, where each tile corresponds to a position. Subsequently, this matrix is used to obtain the new words formed in that turn, and they are validated in the Spanish language dictionary, adding the corresponding points if the word is valid or returning to the previous state otherwise.

6.6.1 About the employed AI

As previously mentioned, AI is a broad field that encompasses various subsets. One is ML, a computational process that uses previously labeled input data to derive rules and produce a result for which it has not been specifically programmed. Within ML, we find DL, and the main difference between this subset and ML is that while the former requires the dataset's features to be specified in advance and understandable by humans, DL algorithms can autonomously extract these features during training. In this way, DL can extract not only the relationship between variables but also the knowledge that gives meaning to this relationship. This is achieved using neural networks with multiple layers, whose neurons adapt during the training process to solve a specific problem.

For these reasons, a DL algorithm, specifically a CNN, has been chosen due to its good metrics when working with raw images. The main steps to obtain a working model were:

- First, to obtain a representative dataset.
- Next, to train a custom CNN.
- And finally, to obtain the metrics and test the model.

6.6.2 Obtaining a Representative Dataset

The best way to obtain a representative dataset is to get samples as close as possible to what the CNN will encounter once in production; it is for this purpose that using an incomplete version of the application in which only the CV step is performed a great number of different game scenarios without perspective were gathered, Figure 29 is one example.

Figure 29. Original Intelect without Perspective

The game scenarios were also taken in different physical locations and at times of the day to avoid overfitting the AI in a certain place and losing the ability to generalize, provoking that the game could only be played during a certain time and in a certain area. Also, to obtain as many samples as possible, it was decided that from each location it will be taken a picture of

- a turn of a regular playthrough with ten random words placed
- a turn where all word tiles were placed in random spots without respecting the rules
- a turn where all word tiles were used but following the rules.

After that, all the game pictures were split into word tiles by cropping based on the well-known game area dimensions, causing a total of 225 unclassified word tile samples to be generated for each game picture. Since five different locations were used, 3375 word tiles were obtained. Then, those pictures needed to be classified by a tedious and manual process of organizing them into different folders according to their labels; Figure 30 shows the organized 'A' label folder.

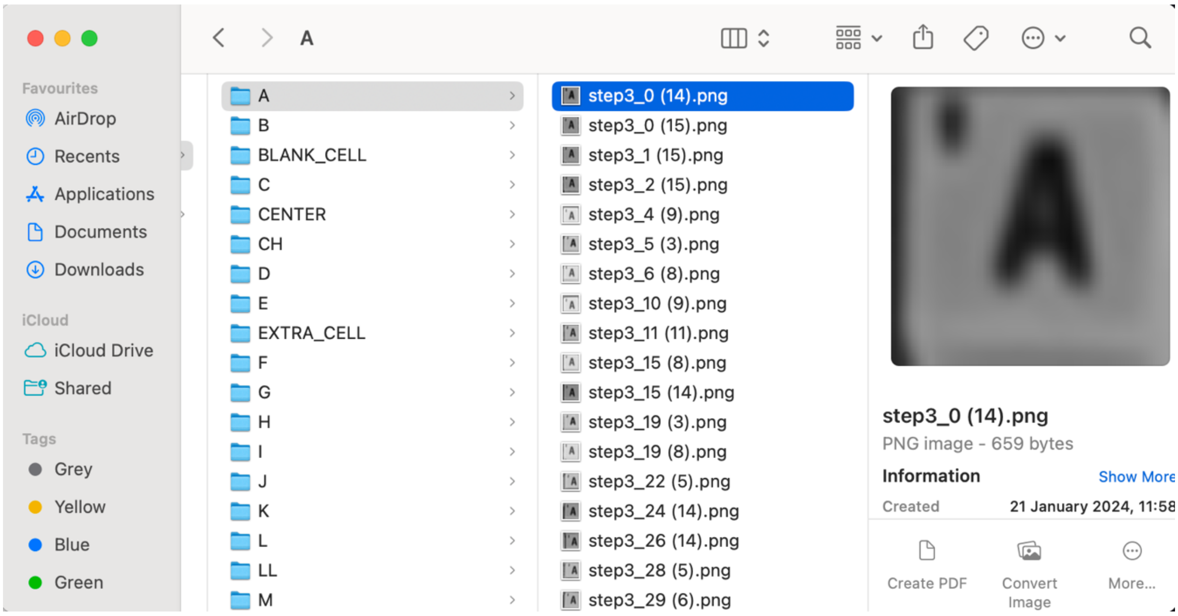


Figure 30. Intelect Deluxe Dataset

However, 3375 pictures are not enough to obtain good metrics since there are 26 different labels, meaning there are only about 130 images per class; therefore, data augmentation was performed to increase it to a more reasonable number.

The data augmentation operations consisted of random rotations, zooms, brightness changes, and contrast changes; the idea behind this was to use only operations that could appear in real life instead of, for example, others like a chromatic aberration. Using this technique, the dataset was severely increased to 5000 unique pictures per class, making the final dataset consist of 130000 images.

Once the dataset was generated, a series of pre-processing operations were applied to the pictures to optimize the future neural network performance since the AI model must be able to run on low-end devices, such as smartphones. The chosen operations were:

- resizing to 32x32
- merging three channels into one, converting the image to a grayscale
- normalization

These operations were chosen because they do not harm the neural network performances; specifically, by grayscaling the images, the CNN can process them more efficiently while reducing computational complexity. There is less information to consider since the color is irrelevant for this classification task. Moreover, resizing the images to 32x32 reduces memory requirements and ensures a standard input for the neural network. Additionally, normalization ensures pixel values are within a standardized range, typically between 0 and 1, making it easier for the neural network to learn patterns. It can be seen in Figure 31 as a sample with pre-processing.

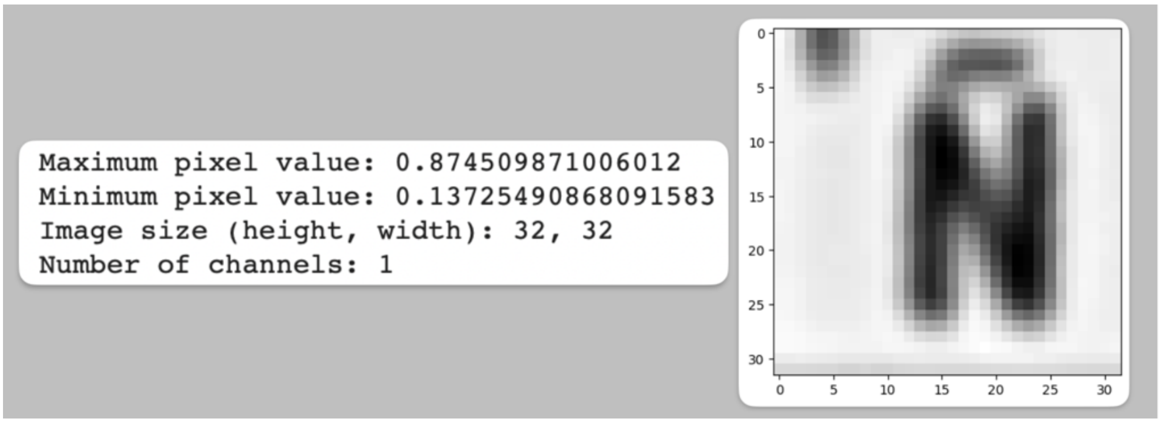


Figure 31. Sample 'ñ' pre-processed

6.6.3 Training of custom CNN

The dataset is divided into three segments to develop the ML model: training, validation, and testing. The training data trains the model on identifying patterns, the validation data helps adjust hyperparameters and avoid overfitting, and the test data assesses the model's effectiveness on new examples.

At this point, the model of the neural network must be created. A trial and error process was undertaken to determine the final architecture of the neural network; it involved experimenting with different configurations of layers, neurons, activation functions, and other parameters. The objective was to find the architecture that best suited the specific task while requiring minimum computational power.

During this process, various architectures and hyperparameters were tested. Each time, the performances were evaluated using validation and test data. This iterative process was repeated until acceptable metrics were reached. Figure 32 shows the final neural network architecture.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_2 (Conv2D)           (None, 30, 30, 29)        290

 max_pooling2d_2 (MaxPoolin  (None, 30, 30, 29)        0
 g2D)

 conv2d_3 (Conv2D)           (None, 28, 28, 64)        16768

 max_pooling2d_3 (MaxPoolin  (None, 28, 28, 64)        0
 g2D)

 flatten_1 (Flatten)         (None, 50176)             0

 dense_1 (Dense)             (None, 128)               6422656

 dense_2 (Dense)             (None, 33)                4257

=================================================================
Total params: 6443971 (24.58 MB)
Trainable params: 6443971 (24.58 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Figure 32. Final neural network structure

As can be seen, this neural network is structured to analyze images. It starts by breaking the images into smaller parts and identifying patterns like edges or textures through convolutional layers. Then, pooling layers reduce the data size while retaining important details. The flattened layer organizes the extracted features into a single list. Dense layers interpret these features, learning complex patterns in a hidden layer with 128 neurons and predicting the probability of each class in the dataset through a final layer with neurons equal to the number of classes. This network essentially takes images, analyses them for features, interprets these features, and predicts what is in the image based on what it has learned.

6.6.4 Final Metrics

After countless trials, the previously seen neural network structure combined with the high-quality dataset obtained a model with the desired metrics; Figure 33 shows the results, reaching almost 100% accuracy in training and validation. The validation split has had outstanding metrics since the beginning due to a lack of data-augmented images; these pictures are harder to predict, causing the training split to be more challenging.

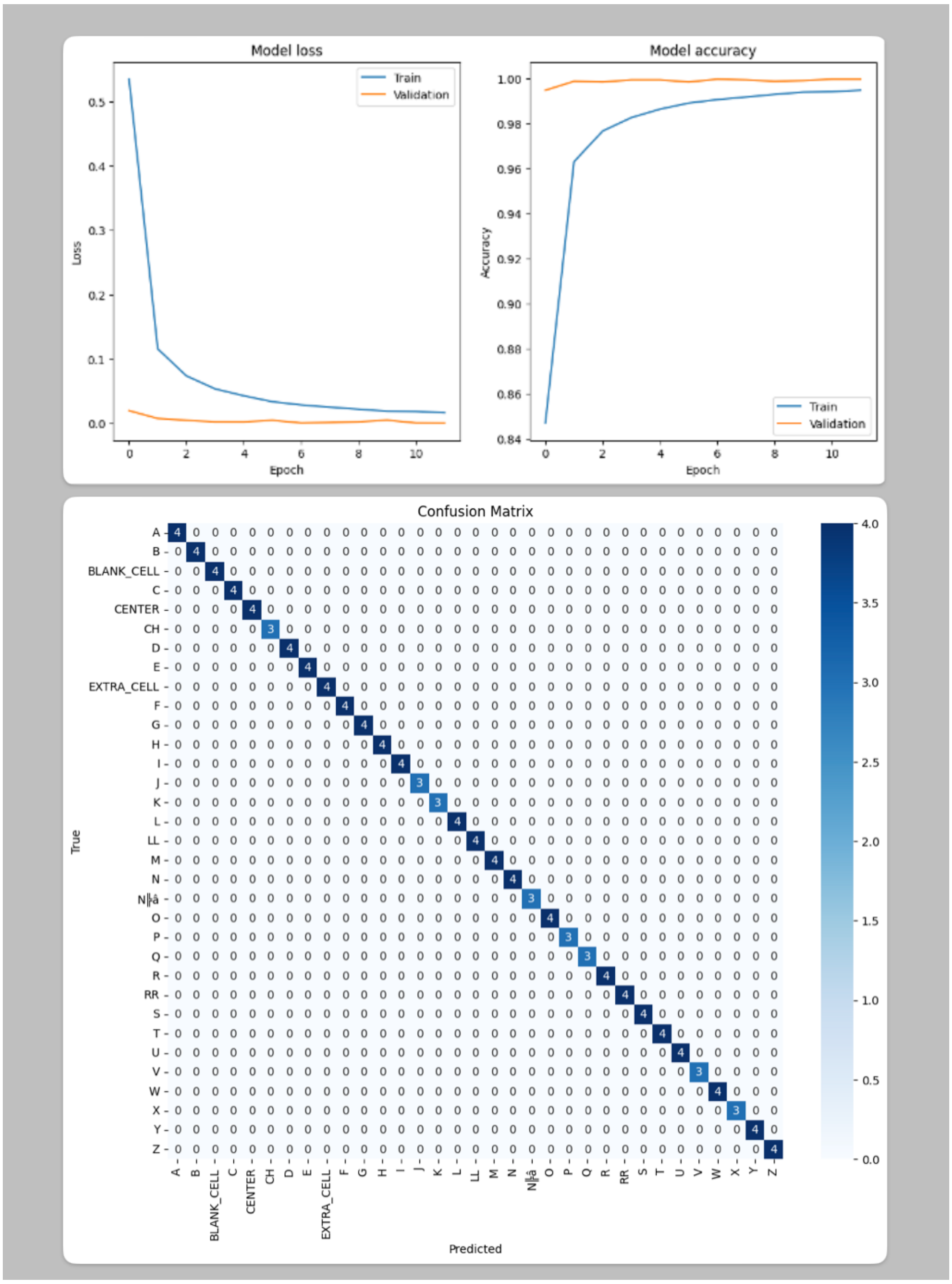


Figure 33. CNN deluxe model metrics

Regarding the last split, the so-called test, the generated model achieved a perfect score mainly because there was a negligible number of word tiles to predict, and these were not data-augmented; the neural network did not have any problem whatsoever. The confusion matrix (Figure 33) is an excellent way to prove it, as explained in the proper theoretical section of this work.

The model is now ready to be deployed, but before that, it must be further evaluated to ensure everything is working as expected (Figure 34); it is for this purpose that a random word tile is selected and predicted, the model returns a list of decimal numbers, each position of this list represents a class, while the number is how confident it is that the given word tile is from a given label, in this case, the model is shown an "h" word tile, and the position in the list with the maximum confidence is also the "h" position; therefore the prediction was correct. Also, note that it takes about 20ms to make a single prediction, which is more than acceptable enough to be used on a mobile device as intended.

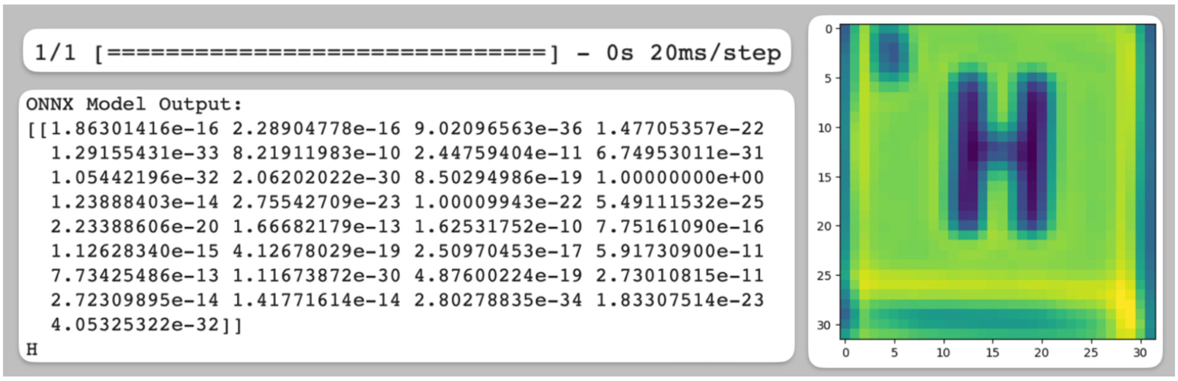


Figure 34. Testing CNN with a random word tile

6.7 Final Product

After obtaining the AI model, it was saved as a .onnx file. The application's frontend was developed using the Unity3D engine due to its robust capabilities in creating experiences across multiple platforms. The deliberate choice of the .onnx file format allowed for seamless integration of the AI model, as it offers interoperability across different deep learning frameworks. Unity3D ensures good performance when using on-device hardware. Additionally, it was selected because an official implementation of OpenCV exists, making it possible to port the entire workflow into the local device. Combining these technologies resulted in a final product (Figure 35) that delivers a compelling and interactive experience, bridging the gap between cutting-edge AI capabilities and user-friendly interface design without needing to be connected to the internet.

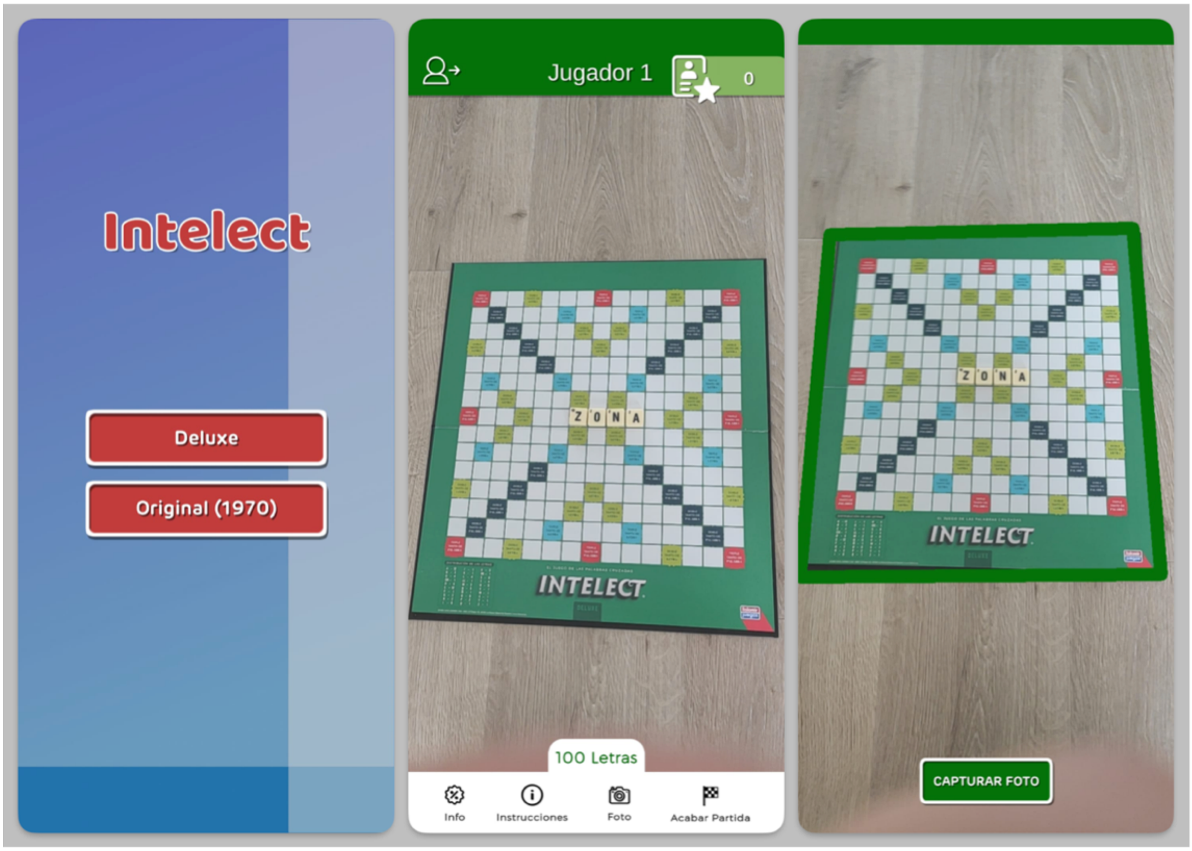


Figure 35. Intelect Mobile App, part I

Figure 35 illustrates the main menu, serving as the gateway for users to select an Intelect game board. This selection process is pivotal as it determines the dimensions required for accurate cropping and loading of the appropriate model. Due to the diverse array of Intelect board variations encompassing dimensions, typography of word tiles, and texture, the AI model must undergo retraining with datasets extracted from each unique board variant. In this practical case, it was done with two sets, the so-called deluxe version and the original Intelect from the 70s.

The middle screenshot provides a glimpse into the primary user interface, offering a range of functionalities beyond board selection. Among these, users can initiate the capture of the game area, a crucial step depicted in the subsequent image. This process allows the AI to capture the game environment precisely, enabling efficient analysis and gameplay assistance. Thus, through these visual representations, users gain insight into the intricate workings of the Intelect system and its adaptive capabilities.

Figure 36 shows how the recognition of a word is performed; the user must wait only a few seconds for the previously explained process to take place in the background, after which a pop-up will show the recognized words; when the user confirms that it was correctly recognized, then the scores are updated.

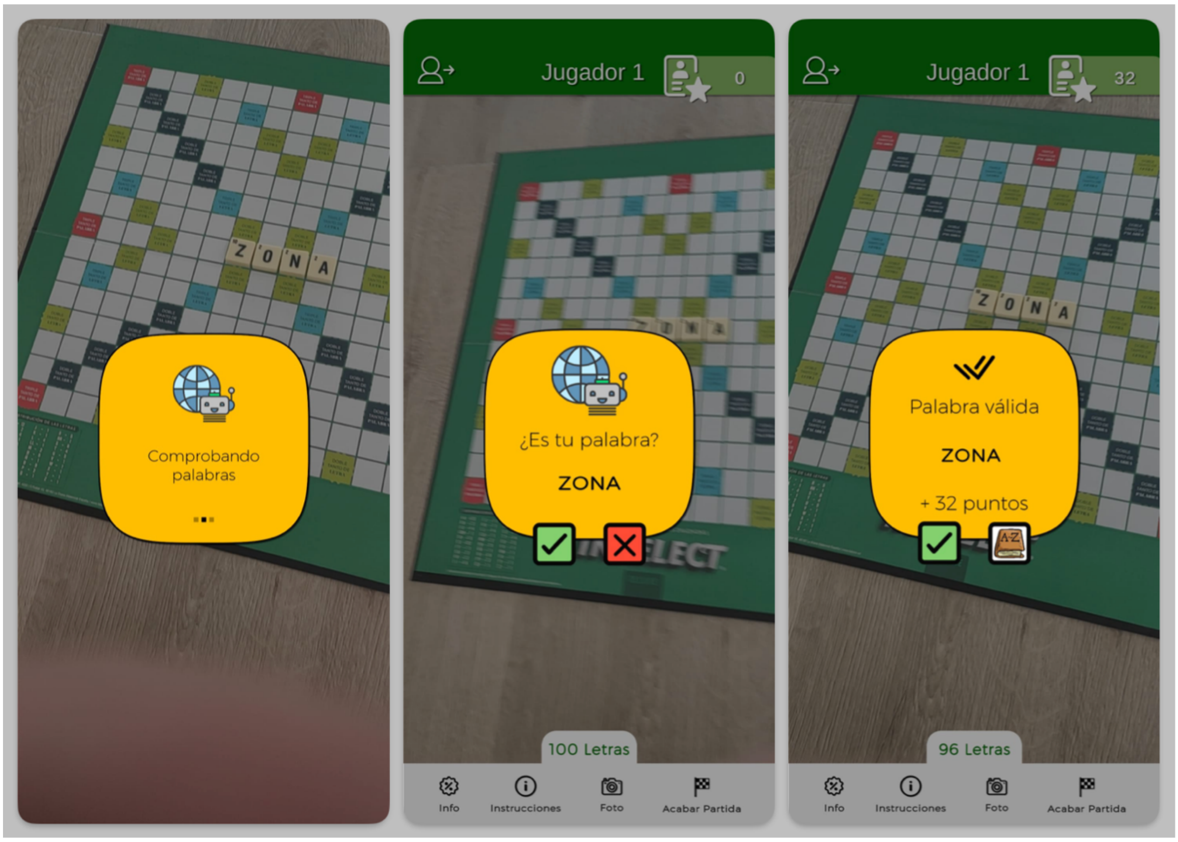


Figure 36. Intelect Deluxe CNN in action

6.8 Future Directions

AI is ever-evolving, presenting new opportunities to enrich educational experiences, particularly in traditional board games. Integrating AI into these games has demonstrated substantial potential to make learning more interactive, personalized, and effective. Several groundbreaking AI advancements and technologies could further revolutionize educational board games, transforming them into highly engaging, multifaceted learning tools.

Advanced Natural Language Processing (NLP)

NLP technologies have made significant strides, enabling machines to understand and generate human language meaningfully and contextually relevantly. By incorporating advanced NLP into educational board games, it's possible to create dynamic interaction models where the game recognizes the words players create and understands their semantic context. For instance, an NLP-enhanced version of Intelect could offer in-game challenges or puzzles based on synonyms, antonyms, or word associations, encouraging players to think critically about language use.

Furthermore, NLP can facilitate real-time language translation features, allowing players from different linguistic backgrounds to engage with the game in their native languages.

This opens a global marketplace for educational board games, making them accessible and educational for a wider audience.

Augmented Reality (AR) Integration

Augmented reality (AR) stands at the forefront of creating immersive educational experiences. By overlaying digital information onto the physical world, AR can transform a standard game of Intelect into a rich, interactive learning environment. Imagine pointing a smartphone or tablet at the game board and seeing 3D animations that illustrate the meaning of words or historical facts about certain terms. Such an application can enhance the visual appeal of learning and accommodate various learning styles, including visual, auditory, and kinesthetic learners.

Additionally, AR could introduce scenario-based learning within the game. Players might be tasked with building vocabulary lists to solve challenges or narratives unfolding in the AR layer, such as repairing a spaceship or solving a mystery. This makes learning fun and contextualizes vocabulary building within practical and imaginative scenarios.

AI-Driven Personalization

The future of educational board games lies in personalization. AI algorithms can analyze a player's performance over time, identifying strengths and weaknesses in their vocabulary or strategic thinking skills. The game could then adapt its difficulty level, provide customized word challenges, or offer tailored educational content that addresses the player's unique learning needs.

Personalization extends beyond adaptive difficulty levels. It could also mean curating game content to align with individual interests or current learning topics. For example, if a player is particularly interested in science, the game could prioritize scientific terms, or if they're studying a specific historical period in school, the game could introduce relevant vocabulary.

Collaborative AI for Team-Based Learning

AI could also facilitate collaborative learning experiences within educational board games. Through the development of intelligent AI opponents or teammates, players can engage in cooperative gameplay, working together to achieve educational goals. These AI characters could pose challenges, offer hints, or simulate real-world interactions, providing a safe and controlled environment for developing teamwork and communication skills.

Moreover, integrating online multiplayer capabilities with AI moderation could allow players from around the globe to connect, compete, and learn together. This enhances the game's educational value and fosters a sense of community and cultural exchange among players.

7 Summary and Conclusions

The intersection of AI and education has significantly improved how students learn and educators teach. From automating administrative tasks to creating personalized tutoring experiences, AI applications are increasingly important in defining the future landscape of education. Therefore, if this technology is applied to classic educational board games, they will be relevant once more.

As digital advancements threaten the relevance of classic board games in the digital age, this work aims to explore how AI can strategically complement traditional games rather than replace them. The focus is on creating a synergy between the strengths of traditional gameplay and the benefits offered by AI and mobile technology. A practical case study was presented using the example of "Intelect," an educational board game focused on vocabulary and mental agility improvement, particularly in Spanish language learning. Integrating AI involves developing a mobile application that utilizes AI capabilities to recognize words formed by players on the physical game board, validate them against a Spanish language dictionary, automate scoring, and track game progress. The process encompasses computer vision techniques, dataset creation, training a custom convolutional neural network (CNN), and integrating the AI model into a mobile app using the Unity3D engine.

Integrating AI with traditional educational board games offers a promising avenue for enriching learning experiences in the digital age. By strategically merging AI technologies with traditional gameplay, it is possible to preserve the essence of time-honored educational tools while leveraging AI's transformative potential. The practical case study demonstrated the feasibility and effectiveness of integrating AI into the Intelect board game, showcasing functionalities such as word recognition, dictionary validation, scoring automation, and game progress tracking. The successful development and deployment of the AI-driven mobile application highlight the potential of AI to enhance traditional board games without requiring constant internet connectivity. This work underscores the importance of embracing technological advancements to evolve educational paradigms and ensure their continued relevance in an increasingly digitalized world.

References

AI Tango. 2024. AI Tango Mario Kart Wii AI | Rainbow DQN - Reinforcement Learning. YouTube. Retrieved on 17 March 2024. Available at https://youtu.be/InnHmVNO07Q.

Alghamdi, Y. 2016. Negative effects of technology on children of today. Oakl Univ. Retrieved on 10 October 2023. Available at https://www.researchgate.net/profile/Yasser-Alghamdi/publication/318851694_Negative_Effects_of_Technology_on_Children_of_Today/links/59819654a6fdccb310051071/Negative-Effects-of-Technology-on-Children-of-Today.pdf

Allery, L. 2014. How to Make Use of Educational Games. Education for Primary Care. Retrieved on 22 September 2023. Available at http://content.ebscohost.com/ContentServer.asp?T=P&P=AN&K=93455035&S=R&D=ehh&EbscoContent=dGJyMNHX8kSeprY4yOvsOLCmr1Gep7JSr664Sa6WxWXS&ContentCustomer=dGJyMO7o44vh5epT69fnhrnb4osA

Alzubaidi, L., Zhang, J., Humaidi, A.J., et al. 2021. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. J Big Data. Retrieved on 9 March 2024. Available at https://doi.org/10.1186/s40537-021-00444-8

Amazon Web Services. 2024. What is deep learning? Retrieved on 7 March 2024. Available at https://aws.amazon.com/what-is/deep-learn-ing/#:~:text=Deep%20learning%20is%20a%20method,produce%20accurate%20insights%20and%20predictions

Amazon. 2011. KLOO Learn French 'Race to Paris'. Amazon. Retrieved on 29 September 2023. Available at https://www.amazon.co.uk/dp/B004UAS472/ref=as_li_tl?ie=UTF8&linkCode=gs2&linkId=VMPOWLD6657OGBYZ&creativeASIN=B004UAS472&tag=mareamazonuk-21&creative=9325&camp=1789

Becker, K. 2021. What is the difference between gamification, serious games, educational games, and game-based learning? Academia Letters. Retrieved on 23 September 2023. Available at https://doi.org/10.20935/AL209

Bird, S., Klein, E., & Loper, E. 2019. Chapter 6: Learning to Classify Text. In Natural Language Processing with Python. Retrieved on 5 March 2024. Available at http://www.nltk.org/book/ch06.html

Bisong, E. 2019. Convolutional Neural Networks (CNN). Building Machine Learning and Deep Learning Models on Google Cloud Platform. Retrieved on 13 March 2024. Available at https://www.semanticscholar.org/paper/Convolutional-Neural-Networks-(CNN)-Bisong/ece1211a653c9da3bfd3fdc7f1ac1ffa010a12d3

Bisong, E. 2019. TensorFlow 2.0 and Keras: Building Machine Learning and Deep Learning Models on Google Cloud Platform. Semantic Scholar. Retrieved on 31 March 2024 Available at https://www.semanticscholar.org/paper/TensorFlow-2.0-and-Keras-Bisong/0b136814352a45c029a09ecf45ab563051a87503

Bleeding Edge Studio. 2023. The Power of Unity for Non-Gaming Applications. LinkedIn. Retrieved on 13 October 2023. Available at: https://www.linkedin.com/pulse/power-unity-non-gaming-applications-bleedingedgestudio/

Campoverde-Ordoñez, B. L., & Espinoza-Freire, E. E. 2019. Incidencia de la tecnología en la pérdida de los juegos tradicionales. Maestro y Sociedad. Retrieved on 25 September 2023 Available at https://maestroysociedad.uo.edu.cu/index.php/MyS/article/view/5079

Cervera, E. 2020. GPU-Accelerated Vision for Robots: Improving System Throughput Using OpenCV and CUDA. IEEE Robotics & Automation Magazine, 27, 151-158. https://www.semanticscholar.org/paper/GPU-Accelerated-Vision-for-Robots%3A-Improving-System-Cervera/56c4c9a90eab1bf11b39362b28dcf6e42392d19a

Chandaliya, R. 2020. Tele Stroke System for Stroke Detection [Thesis, Full-text available]. Retrieved from ResearchGate: https://www.researchgate.net/figure/Relation-between-Artificial-Intelligence-Machine-Learning-and-Deep-Learning-Computer_fig1_342978934

Crypto1. 2024. Gradient Descent Algorithm: How does it Work in Machine Learning? Analytics Vidhya. Retrieved on 11 March 2024. Available at https://www.analyticsvidhya.com/blog/2020/10/how-does-the-gradient-descent-algorithm-work-in-machine-learning/

Das, A. 2017. The Very Basics of Reinforcement Learning. Becoming Human: Artificial Intelligence Magazine. Retrieved on 4 March 2024. Available at https://becominghuman.ai/the-very-basics-of-reinforcement-learning-154f28a79071

Derry, A., Krzywinski, M., & Altman, N. 2023. Convolutional neural networks. Nature Methods. Retrieved on 14 March 2024. Available at https://www.semanticscholar.org/paper/Convolutional-neural-networks-Derry-Krzywinski/183067107a850c6862892ae424bb6a4125f2418c

Deshmukh, O. 2021. Computer Vision. International Journal for Research in Applied Science and Engineering Technology. https://www.semanticscholar.org/paper/Computer-Vision-Deshmukh/d672db7a8fa9eec85c16478ba39393ed1859a659

Despeisse, M. 2018. Teaching sustainability leadership in manufacturing: A reflection on the educational benefits of the board game Factory Heroes. Procedia CIRP. Retrieved on 27 September 2023. Available at https://www.sciencedirect.com/science/article/pii/S2212827117309162

Editors of Encyclopaedia Britannica, T. 2023. Scrabble. Encyclopedia Britannica. Retrieved on 4 October 2023. Available at https://www.britannica.com/sports/Scrabble

Falomir. 2011. Juego de Mesa Intelec De Luxe | Educativo para Mejorar Vocabulario y Ejercitar la Mente | Incluye Marcadores, Fichas de Letras y Reloj de Arena. Amazon. Retrieved on March 5, 2024. Available at https://www.amazon.es/Falomir-32-4002-Intelect-Luxe/dp/B003Z7RBSY?th=1

Fitria, T.N. 2021. Grammarly as AI-powered English Writing Assistant: Students' Alternative for Writing English. The Journal of English Language and Literature. Retrieved on 18 October 2023. Available at https://www.semanticscholar.org/paper/Grammarly-as-AI-powered-English-Writing-Assistant%3A-Fitria/0f1de2c79f263e3a02a079768a99bb7db26e5841

Fyhn, K. 2019. Artificial intelligence - expert systems and the conquest of chess. LinkedIn. Retrieved on 31 March 2024. Available at https://www.linkedin.com/pulse/artificial-intelligence-expert-systems-conquest-chess-karsten-fyhn/

Fábrega, M. n.d. 12 Board Games for Developing Thinking Abilities and Life Skills. Daring to Live Fully: Live the Length and Width of Your Life. Retrieved on 28 September 2023. Available at https://daringtolivefully.com/board-games-and-life-skills

Gan, W., Qi, Z., Wu, J., & Lin, C. 2023. Large Language Models in Education: Vision and Opportunities. 2023 IEEE International Conference on Big Data (BigData). Retrieved on 15 October 2023. Available at https://www.semanticscholar.org/paper/Large-Language-Models-in-Education%3A-Vision-and-Gan-Qi/7757b3346e6578fabcfbc74754df1354e1d197d8

GeeksforGeeks. 2023. Find Co-ordinates of Contours using OpenCV | Python. Geeksfor-Geeks. Retrieved on 4 January 2023 Available at: https://www.geeksforgeeks.org/find-co-ordinates-of-contours-using-opencv-python/

Ghosh, A., Sufian, A., Sultana, F., Chakrabarti, A., & De, D. 2019. Fundamental Concepts of Convolutional Neural Network. Retrieved on 15 March 2024. Available at https://www.semanticscholar.org/paper/Fundamental-Concepts-of-Convolutional-Neural-Ghosh-Sufian/9862617db43723db91040c4d55d78ce3836b62ed

Gimpel, M. 2018. Closeup Photo of Scrabble Game Board. Unsplash. Retrieved on 5 October 2023. Available at https://unsplash.com/photos/closeup-photo-of-scrabble-game-board-mmoyZb1cl0A?utm_content=creditCopyText&utm_medium=referral&utm_source=unsplash

Gujjar, J.P. & Kumar, V. 2021. Google Colaboratory: Tool for Deep Learning and Machine Learning Applications. International Journal in Computer Simulation. Retrieved on 31 March 2024 Available at https://www.semanticscholar.org/paper/Google-Colaboratory-%3A-Tool-for-Deep-Learning-and-Gujjar-Kumar/100bc01605ad12954c03aa863cd1152a4cf041b2

Haas, J.K. 2014. A History of the Unity Game Engine. Semantic Scholar. Retrieved on 31 March 2024 Available at https://www.semanticscholar.org/paper/A-History-of-the-Unity-Game-Engine-Haas/5e6b2255d5b7565d11e71e980b1ca141aeb3391d

Holmes, W., & Tuomi, I. 2022. State of the art and practice in AI in education. European Journal of Education. Retrieved on 13 October 2023. Available at https://doi.org/10.1111/ejed.12533

IBM. 2024. Neural networks. Retrieved on 8 March 2024. Available at https://www.ibm.com/topics/neural-networks

Inuwa, M. 2023. "Is Computer Vision also AI?" LinkedIn, February 15. Available at: https://www.linkedin.com/pulse/computer-vision-also-ai-mobarak-inuwa/

Jin, S. 2024. Application of deep learning in ecological resource research: Theories, methods, and challenges - Scientific Figure on ResearchGate. Retrieved on March 3, 2024. Available at https://www.researchgate.net/figure/Relationship-between-the-capabilities-and-amount-of-data-of-simple-statistical-learning_fig1_340134117

Jingles, R. 2013. What Lessons Can Your Kids Learn from Playing Monopoly? My Chat with Philip E. Orbanes, Author of "Monopoly, Money, and You." Reaching for Greatness Guide. Retrieved on 1 October 2023. Available at https://www.reachingforgreatnessguide.com/blog/what-lessons-can-your-kidslearn-from-playing-monopolymy-chat-with-philip-e-orbanes-author-of-monopoly-money-and-you-by-regina-jingles#.VxLvxnpfeYM

Khaira, M., Ritonga, M., & Halim, S. 2021. The effectiveness of scrabble game media in improving learning outcomes. In Journal of Physics: Conference Series. IOP Publishing. Retrieved on 3 October 2023. Available at https://iopscience.iop.org/article/10.1088/1742-6596/1933/1/012128/meta

Kim, M. L. 2021. Children playing Monopoly. Unsplash. Retrieved on 2 October 2023. Available at https://unsplash.com/photos/a-person-holding-a-book-IumYoH-VeSmI?utm_content=creditCopyText&utm_medium=referral&utm_source=unsplash

Kozlowski, A., & Królak, A. (2009). Teaching image processing and pattern recognition with the Intel OpenCV library [Article, Full-text available]. Retrieved from ResearchGate: https://www.researchgate.net/figure/The-basic-structure-of-the-OpenCV-library_fig1_252458755

Kromydas, B. N.D. Understanding Convolutional Neural Network (CNN): A Complete Guide. Learn OpenCV. Retrieved on 16 March 2024. Available at https://learnopencv.com/understanding-convolutional-neural-networks-cnn/

Kumar, S. 2019. Data Augmentation Increases Accuracy of Your Model — But How? Secure and Private AI Writing Challenge. Published on July 21, 2019. Retrieved on March 3, 2024. Available at https://medium.com/secure-and-private-ai-writing-challenge/data-augmentation-increases-accuracy-of-your-model-but-how-aa1913468722

Kundu, R. 2023. "Image Processing: Techniques, Types, & Applications." V7 Labs Blog. Retrieved on August 3, 2022. Available at: https://www.v7labs.com/blog/image-processing-guide

Lee, H. K., & Raziff, A. R. A. 2021. The impact of technology adoption on the success and failure of two toys industry: Hasbro and Toys R Us. The Journal of Management Theory and Practice (JMTP). Retrieved on 8 October 2023. Available at https://journal.unisza.edu.my/jmtp/index.php/jmtp/article/view/132

Li, J., Li, D., Xiong, C., & Hoi, S. 2022. Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation. arXiv preprint arXiv:2201.12086. Retrieved on 11 October 2023. Available at https://doi.org/10.48550/arXiv.2201.12086

Linares Pellicer, J. 2022a. Introduction to AI. Universitat Politècnica de València, Poliformat. Retrieved on 3 February 2022. Limited availability at https://poliformat.upv.es/access/content/group/PHY_X_2024/Basic%20slides-2022/Introduction%20to%20AI.pdf

Linares Pellicer, J. 2022b. Introduction to Machine Learning. Universitat Politècnica de València, Poliformat. Retrieved on 6 February 2024. Limited availability at https://poliformat.upv.es/access/content/group/PHY_X_2024/Basic%20slides-2022/Introduction%20to%20Machine%20Learning.pdf

Linares Pellicer, J. 2022c. Machine Learning Error Metrics. Universitat Politècnica de València, Poliformat. Retrieved on 25 February 2024. Limited availability at https://poliformat.upv.es/access/content/group/PHY_X_2024/Basic%20slides-2022/Machine%20Learning%20Error%20Metrics.pdf

Linares Pellicer, J. 2022d. Introduction to neural networks and deep learning. Universitat Politècnica de València, Poliformat. Retrieved on 28 February 2024. Limited availability at https://poliformat.upv.es/access/content/group/PHY_X_2024/Basic%20slides-2022/Introduction%20to%20neural%20networks%20and%20deep%20learning.pdf

Linares Pellicer, J. 2022e. CNN. Universitat Politècnica de València, Poliformat. Retrieved on 3 March 2024. Limited availability at https://poliformat.upv.es/access/content/group/PHY_X_2024/Basic%20slides-2022/CNN.pdf

Manaswi, N. 2018. Understanding and Working with Keras. Semanticscholar.org. Retrieved on 31 March 2024 Available at https://www.semanticscholar.org/paper/Understanding-and-Working-with-Keras-Manaswi/11a6cfb183a3f15c8bcaa8953c1bbe1849ca1a62

Mihalek, T. 1996. World chess champion Garry Kasparov (left) playing against IBM's supercomputer Deep Blue in 1996 during the ACM Chess Challenge in Philadelphia. Retrieved on February 4, 2024, Available at https://spectrum.ieee.org/how-ibms-deep-blue-beat-world-champion-chess-player-garry-kasparov

Murtaza's Workshop - Robotics and AI. 2020. Document Scanner OPENCV PYTHON | Beginner Project. [Online Video]. Retrieved on 8 February 2020. Available at: https://www.youtube.com/watch?v=ON_JubFRw8M

Nelson, J. 2020. When to Use Grayscale as a Preprocessing Step. Roboflow Blog. Published on February 5, 2020. Retrieved on March 3, 2024. Available at https://blog.roboflow.com/when-to-use-grayscale-as-a-preprocessing-step/

Nguyen, D.M., & Chen, D. 2016. Photomath – A Mobile App for Algebra Teaching and Tutorials. Retrieved 16 October 2023. Available at https://onlinelibrary.wiley.com/doi/10.1111/ejed.12533

OpenCV Team. 2024. About OpenCV. Retrieved from https://opencv.org/about/

Pain, A. 2024. "Understanding Image Processing in Computer Vision: A Comprehensive Guide." LinkedIn. Retrieved on January 21, 2024. Available at: https://www.linkedin.com/pulse/understanding-image-processing-computer-vision-guide-aritra-pain-fu0lc/

Pandey, M.A. 2023. Computer Vision. International Journal for Research in Applied Science and Engineering Technology. https://www.semanticscholar.org/paper/Computer-Vision-Pandey/0175b060eb0aff699de54ab7cb885a32934453ea

Pandey, N. 2023. "Lesson 2: Understanding Image Processing: Basics and Techniques in Computer Vision." Medium. Retrieved on May 29, 2023. Available at: https://medium.com/@naveenpandey2706/lesson-2-understanding-image-processing-basics-and-techniques-in-computer-vision-c1d7c9763966

Parzuchowski, M. 2022. Chess match. Unsplash. Retrieved on 6 October 2023. Available at https://unsplash.com/photos/brown-wooden-chess-piece-on-brown-wooden-chess-piece-5U7i1R8V9yA?utm_content=creditCopyText&utm_medium=referral&utm_source=unsplash

Pope, L. 2021. Board games as educational tools. Susted. Retrieved on 24 September 2023. Available at http://www.susted.com/wordpress/content/board-games-as-educational-tools_2021_05/

Pulli, K., Baksheev, A., Kornyakov, K., & Eruhimov, V. (2012). Realtime Computer Vision with OpenCV. Queue, 10, 40 - 56. https://www.semanticscholar.org/paper/Realtime-Computer-Vision-with-OpenCV-Pulli-Baksheev/5a3dfc1b7ff2531a5c45e8547cb7ff03849f8f48

Raja, R., & Nagasubramani, P. C. 2018. Impact of modern technology in education. Journal of Applied and Advanced Research. Retrieved on 7 October 2023. Available at https://d1wqtxts1xzle7.cloudfront.net/63887921/Impact_of_modern_technology_in_education20200710-27957-jsmaeg-libre.pdf?1594438050=&response-content-disposi-tion=inline%3B+filename%3DImpact_of_modern_technology_in_education.pdf&Expires=1701345747&Signature=HU4KDnLBcB4FmS1grz5KgaY-pQEmd~1X8PMwGz80L2tSMBzM5RCP0OzaNCRg-sdLBKCSy8QwaXNPDV9P1eCVTjOIQFylw4qDdztxh1zfb4INQy15z5gVi2weAcb1TQXFH7If-FeOE0LV1278IawZysGghzcBGHZOqYmF~vZ7nyl~UQebn1fMyYIZ3ifd-BE9XxZUVnC36LbT6O~jvOz~TtTk0fjGwsKHH2RvCFyN0Y~8o~mfbTNy8r8V0wUYQljJcvlngc1oTwjaYCm~08ojw1NR4h-lRx1s-Fwh71JaFmJDKyZbM4IZC66vKbgybOPWxqBenl-OchyXj7Q5KOJB-Bnw__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA

Saha, S. 2018. A Comprehensive Guide to Convolutional Neural Networks — the ELI5 way. Towards Data Science. Published on December 15, 2018. Retrieved on March 3, 2024. Available at https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Sahir, S. 2019. "Canny Edge Detection Step by Step in Python — Computer Vision." Towards Data Science. Retrieved on January 25, 2019. Available at: https://towardsdatascience.com/canny-edge-detection-step-by-step-in-python-computer-vision-b49c3a2d8123

Shonel. N.D. What does gradient mean in Machine Learning? Quora. Retrieved on 10 March 2024. Available at https://www.quora.com/What-does-gradient-mean-in-Machine-Learn-ing#:~:text=Gradient%20provides%20that%20steepest%20direction,to%20reach%20our%20optimal%20solution

Simplilearn. 2023. Understanding The Machine Learning Process: Key Steps and More. Retrieved on 6 March 2024. Available at https://www.simplilearn.com/what-is-machine-learning-process-article

Skansi, S. 2018. Convolutional Neural Networks. Retrieved on 12 March 2024. Available at https://www.semanticscholar.org/paper/Convolutional-Neural-Networks-Skansi/602993051a5e6f1d18c1317ce7fe061f48a1f2c7

Soegiyarto, M.S., Putri, R.A., & Saputra, S.D. 2022. The Importance of Getting Automated Grammar Feedback via Grammarly, for Increasing Students' English Language Proficiency. Retrieved on 17 October 2023. Available at https://www.semanticscholar.org/paper/The-Importance-of-Getting-Automated-Grammar-via-for-Soegiyarto-Putri/148499645390489c224a9d824a95b0ca51917479

Syed, Abdullah, Mohd., Zin, Ahmad, Aljunid, & Nordin, M.J. 2017. A REVIEW OF INTELLI-GENT TUTORING SYSTEMS IN E-LEARNING. Retrieved on 14 October 2023. Available at https://www.semanticscholar.org/paper/A-REVIEW-OF-INTELLIGENT-TUTORING-SYSTEMS-IN-Syed-Abdullah/6dbf4ec9e88742f2538e25f688a1e4814a519035

Tahiru, F. 2021. AI in Education: A Systematic Literature Review. Journal of Cases on Information Technology (JCIT). Retrieved on 12 October 2023. Available at http://doi.org/10.4018/JCIT.2021010101

Tasnim, R. & Yahya, S. 2013. Playing entrepreneurship: Can games make a difference. Entrepreneurial Practice Review. Retrieved on 26 September 2023. Available at https://d1wqtxts1xzle7.cloudfront.net/31991380/RAHAYU_article_2012-libre.pdf?1392359393=&response-content-disposi-tion=inline%3B+filename%3DPlaying_Entrepreneurship_Can_Games_Make.pdf&Expires=1701074479&Signature=bONjTNTZndIBD3FrsKx-wl6mYLfNOTwiv7xV8j6k-6ftGoBe20Z9QY0mus53TUt51aUpDQ6yUeQFAAsVbIl0~j5B8pti-188uZPbORKv8bkk-kAnRNJOU~TDbfjcNP04UGx~KGD3f3PmrXOhNgjEbguTCY7Jligp8Na5AKur0n23QqvJ-671Gs3bDQ4J4HD2VCkwLSHMPEK6NIs84-zL9Kh~gJYpMwF9~2qhw4q251W253Wqo3JULVbQSTdLYsIzAOPm8Z93DsgW5INRAzX5TzFVA6dU66Trgzr834Imsq7iCprt-GetUKS~ff6KKYnZoRLA5yc780zU9Gnc3IIkHcQA__&Key-Pair-Id=APKAJ-LOHF5GGSLRBV4ZA

World Economic Forum. 2021. Can we embrace the AI revolution and journey towards a brighter future? Retrieved on 9 October 2023. Available at https://www.wefo-rum.org/agenda/2023/09/can-we-embrace-the-ai-revolution-and-journey-towards-a-brighter-future/

AI Tango. 2024. AI Tango Mario Kart Wii AI | Rainbow DQN - Reinforcement Learning. YouTube. Retrieved on 17 March 2024. Available at https://youtu.be/InnHmVNO07Q

Alghamdi, Y. 2016. Negative effects of technology on children of today. Oakl Univ. Retrieved on 10 October 2023. Available at https://www.researchgate.net/profile/Yasser-Al-ghamdi/publication/318851694_Negative_Effects_of_Technology_on_Children_of_Today/links/59819654a6fdccb310051071/Negative-Effects-of-Technology-on-Children-of-Today.pdf

Allery, L. 2014. How to Make Use of Educational Games. Education for Primary Care. Retrieved on 22 September 2023. Available at http://content.ebscohost.com/ContentServer.asp?T=P&P=AN&K=93455035&S=R&D=ehh&EbscoContent=dGJyMNHX8kSeprY4yOvsOLCmr1Gep7JSr664Sa6WxWXS&ContentCustomer=dGJyMO7o44vh5epT69fnhrnb4osA

Alzubaidi, L., Zhang, J., Humaidi, A.J., et al. 2021. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. J Big Data. Retrieved on 9 March 2024. Available at https://doi.org/10.1186/s40537-021-00444-8

Amazon Web Services. 2024. What is deep learning? Retrieved on 7 March 2024. Available at https://aws.amazon.com/what-is/deep-learn-ing/#:~:text=Deep%20learning%20is%20a%20method,produce%20accurate%20insights%20and%20predictions

Amazon. 2011. KLOO Learn French 'Race to Paris'. Amazon. Retrieved on 29 September 2023. Available at https://www.amazon.co.uk/dp/B004UAS472/ref=as_li_tl?ie=UTF8&linkCode=gs2&linkId=VMPOWLD6657OGBYZ&creativeASIN=B004UAS472&tag=mareamazonuk-21&creative=9325&camp=1789

Bayeck, R. Y. 2020. Examining Board Gameplay and Learning: A Multidisciplinary Review of Recent Research. Simulation & Gaming. Retrieved on 15 April 2024 Available at https://journals.sagepub.com/doi/10.1177/1046878119901286

Becker, K. 2021. What is the difference between gamification, serious games, educational games, and game-based learning? Academia Letters. Retrieved on 23 September 2023. Available at https://doi.org/10.20935/AL209

Bird, S., Klein, E., & Loper, E. 2019. Chapter 6: Learning to Classify Text. In Natural Language Processing with Python. Retrieved on 5 March 2024. Available at http://www.nltk.org/book/ch06.html

Bisong, E. 2019. Convolutional Neural Networks (CNN). Building Machine Learning and Deep Learning Models on Google Cloud Platform. Retrieved on 13 March 2024. Available at https://www.semanticscholar.org/paper/Convolutional-Neural-Networks-(CNN)-Bisong/ece1211a653c9da3bfd3fdc7f1ac1ffa010a12d3

Bisong, E. 2019. TensorFlow 2.0 and Keras: Building Machine Learning and Deep Learning Models on Google Cloud Platform. Semantic Scholar. Retrieved on 31 March 2024 Availa-ble at https://www.semanticscholar.org/paper/TensorFlow-2.0-and-Keras-Bisong/0b136814352a45c029a09ecf45ab563051a87503

Bleeding Edge Studio. 2023. The Power of Unity for Non-Gaming Applications. LinkedIn. Retrieved on 13 October 2023. Available at: https://www.linkedin.com/pulse/power-unity-non-gaming-applications-bleedingedgestudio/

Campoverde-Ordoñez, B. L., & Espinoza-Freire, E. E. 2019. Incidencia de la tecnología en la pérdida de los juegos tradicionales. Maestro y Sociedad. Retrieved on 25 September 2023 Available at https://maestroysociedad.uo.edu.cu/index.php/MyS/article/view/5079

Cervera, E. 2020. GPU-Accelerated Vision for Robots: Improving System Throughput Using OpenCV and CUDA. IEEE Robotics & Automation Magazine, 27, 151-158. Retrieved on 18 February 2024. Available at https://www.semanticscholar.org/paper/GPU-Accelerated-Vision-for-Robots%3A-Improving-System-Cervera/56c4c9a90eab1bf11b39362b28dcf6e42392d19a

Chandaliya, R. 2020. Tele Stroke System for Stroke Detection. Researchgate. Retrieved on 1 April 2024. Available at https://www.researchgate.net/figure/Relation-between-Artificial-Intelligence-Machine-Learning-and-Deep-Learning-Computer_fig1_342978934

Crypto1. 2024. Gradient Descent Algorithm: How does it Work in Machine Learning? Analytics Vidhya. Retrieved on 11 March 2024. Available at https://www.analyticsvidhya.com/blog/2020/10/how-does-the-gradient-descent-algorithm-work-in-machine-learning/

Das, A. 2017. The Very Basics of Reinforcement Learning. Becoming Human: Artificial Intelligence Magazine. Retrieved on 4 March 2024. Available at https://becominghuman.ai/the-very-basics-of-reinforcement-learning-154f28a79071

Derry, A., Krzywinski, M., & Altman, N. 2023. Convolutional neural networks. Nature Methods. Retrieved on 14 March 2024. Available at https://www.semanticscholar.org/paper/Convolutional-neural-networks-Derry-Krzywinski/183067107a850c6862892ae424bb6a4125f2418c

Deshmukh, O. 2021. Computer Vision. International Journal for Research in Applied Science and Engineering Technology. Retrieved on 1 April 2024. Available at https://www.semanticscholar.org/paper/Computer-Vision-Deshmukh/d672db7a8fa9eec85c16478ba39393ed1859a659

Despeisse, M. 2018. Teaching sustainability leadership in manufacturing: A reflection on the educational benefits of the board game Factory Heroes. Procedia CIRP. Retrieved on 27 September 2023. Available at https://www.sciencedirect.com/science/article/pii/S2212827117309162

Editors of Encyclopaedia Britannica, T. 2023. Scrabble. Encyclopedia Britannica. Retrieved on 4 October 2023. Available at https://www.britannica.com/sports/Scrabble

Falomir. 2011. Juego de Mesa Intelec De Luxe | Educativo para Mejorar Vocabulario y Ejercitar la Mente | Incluye Marcadores, Fichas de Letras y Reloj de Arena. Amazon. Retrieved on March 5, 2024. Available at https://www.amazon.es/Falomir-32-4002-Intelect-Luxe/dp/B003Z7RBSY?th=1

Fitria, T.N. 2021. Grammarly as AI-powered English Writing Assistant: Students' Alternative for Writing English. The Journal of English Language and Literature. Retrieved on 18 October 2023. Available at https://www.semanticscholar.org/paper/Grammarly-as-AI-powered-English-Writing-Assistant%3A-Fitria/0f1de2c79f263e3a02a079768a99bb7db26e5841

Fyhn, K. 2019. Artificial intelligence - expert systems and the conquest of chess. LinkedIn. Retrieved on 31 March 2024. Available at https://www.linkedin.com/pulse/artificial-intelligence-expert-systems-conquest-chess-karsten-fyhn/

Fábrega, M. n.d. 12 Board Games for Developing Thinking Abilities and Life Skills. Daring to Live Fully: Live the Length and Width of Your Life. Retrieved on 28 September 2023. Available at https://daringtolivefully.com/board-games-and-life-skills

Gan, W., Qi, Z., Wu, J., & Lin, C. 2023. Large Language Models in Education: Vision and Opportunities. 2023 IEEE International Conference on Big Data (BigData). Retrieved on 15 October 2023. Available at https://www.semanticscholar.org/paper/Large-Language-Models-in-Education%3A-Vision-and-Gan-Qi/7757b3346e6578fabcfbc74754df1354e1d197d8

GeeksforGeeks. 2023. Find Co-ordinates of Contours using OpenCV | Python. Geeks-for-Geeks. Retrieved on 4 January 2023 Available at: https://www.geeksforgeeks.org/find-co-ordinates-of-contours-using-opencv-python/

Ghosh, A., Sufian, A., Sultana, F., Chakrabarti, A., & De, D. 2019. Fundamental Concepts of Convolutional Neural Network. Retrieved on 15 March 2024. Available at https://www.semanticscholar.org/paper/Fundamental-Concepts-of-Convolutional-Neural-Ghosh-Sufian/9862617db43723db91040c4d55d78ce3836b62ed

Gimpel, M. 2018. Closeup Photo of Scrabble Game Board. Unsplash. Retrieved on 5 October 2023. Available at https://unsplash.com/photos/closeup-photo-of-scrabble-game-board-mmoyZb1cI0A?utm_content=creditCopyText&utm_medium=referral&utm_source=unsplash

Gujjar, J.P. & Kumar, V. 2021. Google Colaboratory: Tool for Deep Learning and Machine Learning Applications. International Journal in Computer Simulation. Retrieved on 31

March 2024 Available at https://www.semanticscholar.org/paper/Google-Colaboratory-%3A-Tool-for-Deep-Learning-and-Gujjar-Kumar/100bc01605ad12954c03aa863cd1152a4cf041b2

Haas, J.K. 2014. A History of the Unity Game Engine. Semantic Scholar. Retrieved on 31 March 2024 Available at https://www.semanticscholar.org/paper/A-History-of-the-Unity-Game-Engine-Haas/5e6b2255d5b7565d11e71e980b1ca141aeb3391d

Holmes, W., & Tuomi, I. 2022. State of the art and practice in AI in education. European Journal of Education. Retrieved on 13 October 2023. Available at https://doi.org/10.1111/ejed.12533

IBM. 2024. Neural networks. Retrieved on 8 March 2024. Available at https://www.ibm.com/topics/neural-networks

Imani, K., & Mulyanto, A. 2023. World Education Website Localization Using A Culture-Based Design Approach. 2023 International Conference on Electrical Engineering and Informatics (ICEEI). Retrieved on 15 April 2024 Available at https://ieeexplore.ieee.org/document/10346791

Inuwa, M. 2023. "Is Computer Vision also AI?" LinkedIn. Retrieved on 1 April 2024. Availa-ble at: https://www.linkedin.com/pulse/computer-vision-also-ai-mobarak-inuwa/

Jin, S. 2024. Application of deep learning in ecological resource research: Theories, methods, and challenges - Scientific Figure on ResearchGate. Retrieved on March 3, 2024. Available at https://www.researchgate.net/figure/Relationship-between-the-capabilities-and-amount-of-data-of-simple-statistical-learning_fig1_340134117

Jingles, R. 2013. What Lessons Can Your Kids Learn from Playing Monopoly? My Chat with Philip E. Orbanes, Author of "Monopoly, Money, and You." Reaching for Greatness Guide. Retrieved on 1 October 2023. Available at https://www.reachingforgreatnessguide.com/blog/what-lessons-can-your-kidslearn-from-playing-monopolymy-chat-with-philip-e-orbanes-author-of-monopoly-money-and-you-by-regina-jingles#.VxLvxnpfeYM

Khaira, M., Ritonga, M., & Halim, S. 2021. The effectiveness of scrabble game media in improving learning outcomes. In Journal of Physics: Conference Series. IOP Publishing. Retrieved on 3 October 2023. Available at https://iopscience.iop.org/article/10.1088/1742-6596/1933/1/012128/meta

Kim, M. L. 2021. Children playing Monopoly. Unsplash. Retrieved on 2 October 2023. Available at https://unsplash.com/photos/a-person-holding-a-book-IumYoH-VeSmI?utm_content=creditCopyText&utm_medium=referral&utm_source=unsplash

Kozlowski, A., & Królak, A. 2009. Teaching image processing and pattern recognition with the Intel OpenCV library. ResearchGate. Retrieved on 1 April 2024. Available at: https://www.researchgate.net/figure/The-basic-structure-of-the-OpenCV-library_fig1_252458755

Kromydas, B. N.D. Understanding Convolutional Neural Network (CNN): A Complete Guide. Learn OpenCV. Retrieved on 16 March 2024. Available at https://learnopencv.com/understanding-convolutional-neural-networks-cnn/

Kumar, S. 2019. Data Augmentation Increases Accuracy of Your Model — But How? Secure and Private AI Writing Challenge. Published on July 21, 2019. Retrieved on March 3, 2024. Available at https://medium.com/secure-and-private-ai-writing-challenge/data-augmentation-increases-accuracy-of-your-model-but-how-aa1913468722

Kundu, R. 2023. "Image Processing: Techniques, Types, & Applications." V7 Labs Blog. Retrieved on August 3, 2022. Available at: https://www.v7labs.com/blog/image-processing-guide

Lampou, R. 2023. The Integration of Artificial Intelligence in Education: Opportunities and Challenges. Review of Artificial Intelligence in Education. Retrieved on 15 April 2024 Available at https://educationai-review.org/revista/article/view/15

Lee, H. K., & Raziff, A. R. A. 2021. The impact of technology adoption on the success and failure of two toys industry: Hasbro and Toys R Us. The Journal of Management Theory and Practice (JMTP). Retrieved on 8 October 2023. Available at https://journal.unisza.edu.my/jmtp/index.php/jmtp/article/view/132

Li, J., Li, D., Xiong, C., & Hoi, S. 2022. Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation. arXiv preprint arXiv:2201.12086. Retrieved on 11 October 2023. Available at https://doi.org/10.48550/arXiv.2201.12086

Linares Pellicer, J. 2022a. Introduction to AI. Universitat Politècnica de València, Poliformat. Retrieved on 3 February 2022. Limited availability at https://poliformat.upv.es/access/content/group/PHY_X_2024/Basic%20slides-2022/Introduction%20to%20AI.pdf

Linares Pellicer, J. 2022b. Introduction to Machine Learning. Universitat Politècnica de València, Poliformat. Retrieved on 6 February 2024. Limited availability at https://poliformat.upv.es/access/content/group/PHY_X_2024/Basic%20slides-2022/Introduction%20to%20Machine%20Learning.pdf

Linares Pellicer, J. 2022c. Machine Learning Error Metrics. Universitat Politècnica de València, Poliformat. Retrieved on 25 February 2024. Limited availability at https://poliformat.upv.es/access/content/group/PHY_X_2024/Basic%20slides-2022/Machine%20Learning%20Error%20Metrics.pdf

Linares Pellicer, J. 2022d. Introduction to neural networks and deep learning. Universitat Politècnica de València, Poliformat. Retrieved on 28 February 2024. Limited availability at https://poliformat.upv.es/access/content/group/PHY_X_2024/Basic%20slides-2022/Introduction%20to%20neural%20networks%20and%20deep%20learning.pdf

Linares Pellicer, J. 2022e. CNN. Universitat Politècnica de València, Poliformat. Retrieved on 3 March 2024. Limited availability at https://poliformat.upv.es/access/content/group/PHY_X_2024/Basic%20slides-2022/CNN.pdf

Manaswi, N. 2018. Understanding and Working with Keras. Semanticscholar.org. Retrieved on 31 March 2024 Available at https://www.semanticscholar.org/paper/Understanding-and-Working-with-Keras-Manaswi/11a6cfb183a3f15c8bcaa8953c1bbe1849ca1a62

Mihalek, T. 1996. World chess champion Garry Kasparov (left) playing against IBM's supercomputer Deep Blue in 1996 during the ACM Chess Challenge in Philadelphia. Retrieved on February 4, 2024, Available at https://spectrum.ieee.org/how-ibms-deep-blue-beat-world-champion-chess-player-garry-kasparov

Murtaza's Workshop - Robotics and AI. 2020. Document Scanner OPENCV PYTHON | Beginner Project. YouTube. Retrieved on 12 March 2024. Available at: https://www.youtube.com/watch?v=ON_JubFRw8M

Nelson, J. 2020. When to Use Grayscale as a Preprocessing Step. Roboflow Blog. Published on February 5, 2020. Retrieved on March 3, 2024. Available at https://blog.roboflow.com/when-to-use-grayscale-as-a-preprocessing-step/

Nguyen, D.M., & Chen, D. 2016. Photomath – A Mobile App for Algebra Teaching and Tutorials. Retrieved on 16 October 2023. Available at https://onlinelibrary.wiley.com/doi/10.1111/ejed.12533

OpenCV Team. 2024. About OpenCV. OpenCV. Retrieved on 30 March 2024. Available at https://opencv.org/about/

Pain, A. 2024. Understanding Image Processing in Computer Vision: A Comprehensive Guide. LinkedIn. Retrieved on 21 January 2024. Available at: https://www.linkedin.com/pulse/understanding-image-processing-computer-vision-guide-aritra-pain-fu0lc/

Pandey, M.A. 2023. Computer Vision. International Journal for Research in Applied Science and Engineering Technology. Retrieved on 24 January 2024. Available at https://www.semanticscholar.org/paper/Computer-Vision-Pandey/0175b060eb0aff699de54ab7cb885a32934453ea

Pandey, N. 2023. Lesson 2: Understanding Image Processing: Basics and Techniques in Computer Vision. Medium. Retrieved on May 29, 2023. Available at: https://medium.com/@naveenpandey2706/lesson-2-understanding-image-processing-basics-and-techniques-in-computer-vision-c1d7c9763966

Papadimitriou, S., Mougiakou, E., & Virvou, M. K. 2019. Smart educational games and Consent under the scope of General Data Protection Regulation. 2019 International Conference on Information, Intelligence, Systems and Applications (IISA). Retrieved on 15 April 2024 Available at https://ieeexplore.ieee.org/document/8900687

Parzuchowski, M. 2022. Chess match. Unsplash. Retrieved on 6 October 2023. Available at https://unsplash.com/photos/brown-wooden-chess-piece-on-brown-wooden-chess-piece-5U7i1R8V9yA?utm_content=creditCopyText&utm_medium=referral&utm_source=unsplash

Pope, L. 2021. Board games as educational tools. Susted. Retrieved on 24 September 2023. Available at http://www.susted.com/wordpress/content/board-games-as-educational-tools_2021_05/

Price, C. B., & Moore, J. S. 2008. Approaches to Developing Educational Resources Using AI Embedded in Computer Game Technology. A Case Study: Primary School Literacy. Retrieved on 15 April 2024 Available at https://www.semanticscholar.org/paper/Approaches-to-Developing-Educational-Resources-AI-A-Price-Moore/459e5605244b13ea65a855777a76359bcc009f04

Pulli, K., Baksheev, A., Kornyakov, K., & Eruhimov, V. 2012. Realtime Computer Vision with OpenCV. Queue. Retrieved on 1 April 2024. Available at: https://www.semanticscholar.org/paper/Realtime-Computer-Vision-with-OpenCV-Pulli-Baksheev/5a3dfc1b7ff2531a5c45e8547cb7ff03849f8f48

Raja, R., & Nagasubramani, P. C. 2018. Impact of modern technology in education. Journal of Applied and Advanced Research. Retrieved on 7 October 2023. Available at https://d1wqtxts1xzle7.cloudfront.net/63887921/Impact_of_modern_technology_in_education20200710-27957-jsmaeg-libre.pdf?1594438050=&response-content-disposi-tion=inline%3B+filename%3DImpact_of_modern_technology_in_education.pdf&Expires=1701345747&Signature=HU4KDnLBcB4FmS1grz5KgaY-pQEmd~1X8PMwGz80L2tSMBzM5RCP0OzaNCRg-sdLBKCSy8QwaXNPDV9P1eCVTjOlQFylw4qDdztxh1zfb4INQy15z5gVi2weAcb1TQXFH7lf-FeOE0LV1278lawZysGghzcBGHZOqYmF~vZ7nyl~UQebn1fMyYIZ3ifd-BE9XxZUVnC36LbT6O~jvOz~TtTk0fjGwsKHH2RvCFyN0Y~8o~mfbTNy8r8V0wUYQljJcvlngc1oTwjaYCm~08ojw1NR4h-lRx1s-Fwh71JaFmJDKyZbM4IZC66vKbgybOPWxqBenl-OchyXj7Q5KOJB-Bnw__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA

Saha, S. 2018. A Comprehensive Guide to Convolutional Neural Networks — the ELI5 way. Towards Data Science. Published on December 15, 2018. Retrieved on March 3, 2024. Available at https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Sahir, S. 2019. "Canny Edge Detection Step by Step in Python — Computer Vision." Towards Data Science. Retrieved on January 25, 2019. Available at: https://towardsdatascience.com/canny-edge-detection-step-by-step-in-python-computer-vision-b49c3a2d8123

Shonel. N.D. What does gradient mean in Machine Learning? Quora. Retrieved on 10 March 2024. Available at https://www.quora.com/What-does-gradient-mean-in-Machine-Learn-ing#:~:text=Gradient%20provides%20that%20steepest%20direction,to%20reach%20our%20optimal%20solution

Simplilearn. 2023. Understanding The Machine Learning Process: Key Steps and More. Retrieved on 6 March 2024. Available at https://www.simplilearn.com/what-is-machine-learning-process-article

Skansi, S. 2018. Convolutional Neural Networks. Retrieved on 12 March 2024. Available at https://www.semanticscholar.org/paper/Convolutional-Neural-Networks-Skansi/602993051a5e6f1d18c1317ce7fe061f48a1f2c7

Soegiyarto, M.S., Putri, R.A., & Saputra, S.D. 2022. The Importance of Getting Automated Grammar Feedback via Grammarly, for Increasing Students' English Language Proficiency. Retrieved on 17 October 2023. Available at https://www.semanticscholar.org/paper/The-Importance-of-Getting-Automated-Grammar-via-for-Soegiyarto-Putri/148499645390489c224a9d824a95b0ca51917479

Syed, Abdullah, Mohd., Zin, Ahmad, Aljunid, & Nordin, M.J. 2017. A REVIEW OF INTELLI-GENT TUTORING SYSTEMS IN E-LEARNING. Retrieved on 14 October 2023. Available at https://www.semanticscholar.org/paper/A-REVIEW-OF-INTELLIGENT-TUTORING-SYSTEMS-IN-Syed-Abdullah/6dbf4ec9e88742f2538e25f688a1e4814a519035

Tahiru, F. 2021. AI in Education: A Systematic Literature Review. Journal of Cases on Information Technology (JCIT). Retrieved on 12 October 2023. Available at http://doi.org/10.4018/JCIT.2021010101

Tasnim, R. & Yahya, S. 2013. Playing entrepreneurship: Can games make a difference. Entrepreneurial Practice Review. Retrieved on 26 September 2023. Available at https://d1wqtxts1xzle7.cloudfront.net/31991380/RAHAYU_article_2012-libre.pdf?1392359393=&response-content-disposi-tion=inline%3B+filename%3DPlaying_Entrepreneurship_Can_Games_Make.pdf&Expires=1701074479&Signature=bONjTNTZndIBD3FrsKx-wl6mYLfNOTwiv7xV8j6k-6ftGoBe20Z9QY0mus53TUt51aUpDQ6yUeQFAAsVbIl0~j5B8pti-188uZPbORKv8bkk-kAnRNJOU~TDbfjcNP04UGx~KGD3f3PmrXOhNgjEbguTCY7Jligp8Na5AKur0n23QqvJ-671Gs3bDQ4J4HD2VCkwLSHMPEK6NIs84-zL9Kh~gJYpMwF9~2qhw4q251W253Wqo3JULVbQSTdLYsIzAOPm8Z93DsgW5lNRAzX5TzFVA6dU66Trgzr834Imsq7iCprt-GetUKS~ff6KKYnZoRLA5yc780zU9Gnc3IIkHcQA__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA

World Economic Forum. 2021. Can we embrace the AI revolution and journey towards a brighter future? Retrieved on 9 October 2023. Available at https://www.weforum.org/agenda/2023/09/can-we-embrace-the-ai-revolution-and-journey-towards-a-brighter-future/