FRANKIE: AN OPEN-SOURCE EDUCATIONAL ROBOT FOR TEACHING ROBOTICS AND ARTIFICIAL INTELLIGENCE

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Abstract

This paper presents FRANKIE, a low-cost, open-source educational robot designed to support introductory teaching of AI and robotics. The proposal addresses the need for educational resources that combine ease of use, technical feasibility, and the potential to stimulate logical reasoning, understanding of AI algorithm functioning (neural networks) among elementary and secondary school students. As a result of the work, it was observed that the students understood how the RNSP WiSARD trains and classifies labels and that the strategies implemented provided zones of proximal development, leading students to a continuous learning process throughout the activities carried out.

Keywords: Artificial Intelligence in education, Neural Network, Educational Robotics, Technologies in education.

1 INTRODUCTION

Artificial Intelligence (AI) is present in the daily life of 21st-century citizens, whether through their mobile devices or through interaction with a variety of intelligent artifacts In today's technological context, AI has been applied in areas ranging from Marketing, Medicine, Engineering, Politics, Human Resources, and Financial Services to leisure activities, including games and Social Networks Because this technology is embedded in many sectors of society, through increasingly ubiquitous computing, the relationship of ordinary citizens with AI has taken place in a passive manner, either as direct or indirect users. Many individuals use smart devices without realizing that this technology advances through interactions with human beings, with the environment in which they live, and through the collection, storage, and analysis of data.

Users generally lack a critical understanding of how these interactions expand the power of intelligent artifacts. This lack of understanding is partly due to the fact that the field of application of this technology has expanded considerably in a short period of time. This scenario highlights the need for technological literacy initiatives aimed at preparing citizens for a reality in which technologies such as Big Data, the Internet of Things, and Artificial Intelligence will be increasingly used to provide solutions to human needs, making life easier, but also holding the power to impact labor relations, the economy, and politics [1].

In this regard, basic education becomes an important space for addressing this topic and introducing the key concepts that underpin AI [2]. Meanwhile, the teaching of programming through the use of educational robotics resources has become increasingly popular, expanding Computer Science activities in public and private formal education institutions, and emerging as a "gateway" to AI literacy initiatives [3] [4]. This reality points to the need for developing teaching and learning strategies to introduce AI education in basic education.

As a response to this demand, the proposal for developing the low-cost robotic device FRANKIE emerges. The robot includes actuators and sensors such as a camera, ultrasonic sensors, motors, and wheels for mobility, all connected to the Raspberry Pi single-board computer, which enables interaction with the environment. The robot serves as a resource for electronic prototyping, exploring the ideas of neural networks and as a platform for programming in Python, the language in which the Frankie codes were developed. The use of the robot aims to increase students' motivation by creating an environment of collaboration and engagement, through challenges proposed during workshops to verify whether the actions carried out by the device correspond to those expected by the learners in the given environment.

In the following sections, we first describe the design and technical specifications of the Frankie robot, highlighting its components, functionalities, and the rationale behind its development as an accessible tool for AI and robotics education (Section 2). Next, we present the methodological framework of the experiment conducted with secondary school students from a public school in Rio de Janeiro (Section 3). We then present the main results obtained, focusing on students' engagement, learning outcomes, and perceptions of working with Frankie (Section 4). Finally, in Section 5 we conclude the work pointing to some implications of these findings for AI literacy initiatives in basic education.

2 FRANKIE PLATFORM

WiSARD is a model of Machine Learning, specifically a type of WNN designed for pattern classification. It is based on Random Access Memory (RAM) and operates as a single-layer neural network [5]. Its simplicity and efficiency come from requiring fewer operations during training and classification, making it lightweight and easy to execute [6].

The operations are mainly based on binary logic, making it accessible for high school students who have basic knowledge of mathematical operations like percentages and binary image representation. Key skills required include pattern recognition, combinatorial thinking, and understanding random processes. The model comprises several important components:

- Retina: A matrix of binary pixels (m x p), where the image patterns are reshaped into a vector of k pixels.
- Tuples: Ordered sets of n bits, randomly selected from the image pixels.
- Neuron: Each neuron in the Weightless Discriminator Device (WDD) functions as a RAM unit, receiving n-bit tuples as input, and having 2^n memory locations.
- Discriminator: A single-layer network of N RAM neurons, each learning and recognizing subsets of a pattern linked to a specific class.
- Adder: This computes the similarity between the input and learned pattern, helping identify the correct class [7].

WiSARD is a supervised weightless neural network, meaning each training pattern is assigned to a specific class [5] [8]. During training, the Discriminator updates neurons based on the binary input pattern. Initially, each neuron's memory content is set to zero, and during training, the memory address, determined by the randomly chosen n bits from the pattern, is incremented.

For example, in a case with a retina of 12 pixels and an input pattern of 3 bits, the Discriminator is made up of 4 neurons, each containing 2^3 memory addresses. Dark pixels on the retina are represented by 1, and light pixels by 0. When a tuple consisting of two dark pixels and one light pixel is processed, the memory address of the first neuron is updated from 0 to 1. This process continues for the other tuples, allowing the Discriminator to learn the pattern associated with a particular class.

WiSARD's ability to classify patterns with such simplicity, combined with its use of binary operations, makes it particularly useful in educational contexts, especially for introducing students to AI and machine learning concepts. Fig. 1 presents a possible approach for training the representation of the letter T in uppercase.

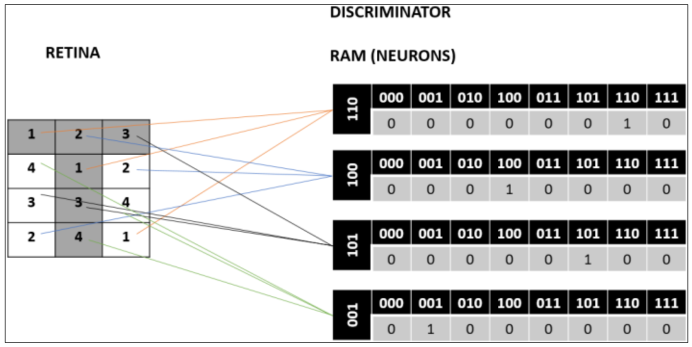

Figure 1. Discriminator of the "T" label with 8-bit memories - First training stage

2.1 Classification Process

In the classification phase (Fig. 2), the neurons' addresses are derived from pixel tuples, following the same process used during training. The new label is input into the trained Discriminator, which uses a similarity measure to classify it. This measure is calculated by the Adder, which counts the number of neurons whose memory positions are addressed by the pixel tuples [5]. The final value from the Adder represents the Discriminator's output.

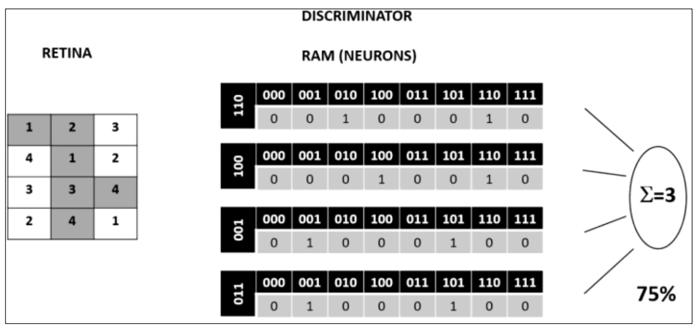

Figure 2.Classification of the trained label - 75% trust

For each tuple, the neuron's memory content at the addressed location is evaluated. If the memory contains a 1, the neuron outputs 1; otherwise, it outputs 0. The classification confidence is determined by the ratio of the Adder's output to the total number of neurons. This ratio, referred to as "Trust," reflects the probability that the classified label matches the trained one.

2.2 Frankie Platform: Robotic Device

The Frankie platform is an innovative example of integrating Educational Robotics (ER) with Artificial Intelligence (AI), assisting students connect theoretical concepts to real-world applications. ER allows students to experiment with real-life simulations, addressing contemporary challenges such as industry innovations and safe human-machine interactions. The Frankie robot achieves this through the use of Machine Learning algorithms, specifically WiSARD, alongside sensors and actuators, enabling interaction with its environment (Fig. 3).

Hardware Components - Frankie's hardware is designed to be easily replicable, with a total cost of around $125. The robot detects objects and classifies pre-trained images to autonomously make movement decisions. The robot is powered by a Raspberry Pi 3, a compact single-board computer with a 1.2GHz quad-core processor, 1GB of RAM, and 64-bit instruction support. The Raspberry Pi allows for real-time execution of Python scripts and connects to external peripherals like a monitor or keyboard via HDMI and USB ports.

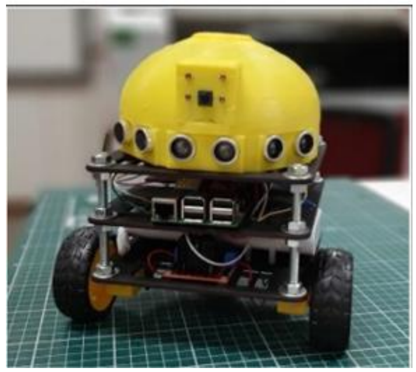

Figure 3. Frankie Robotic Device

Frankie Robotic Device Code - The Frankie robotic device is operated by a Raspberry Pi 3, a single-board minicomputer with a compact form factor, approximately the size of a credit card. It is equipped with a 1.2GHz quad-core processor, supports 64-bit instructions, and has 1GB of RAM. These specifications allow real-time execution of Python scripts, facilitating efficient computation and image processing. Peripheral devices such as a monitor, keyboard, and mouse can be connected to the Raspberry Pi via HDMI and USB ports.

The Raspberry Pi's GPIO ports are programmatically controlled through Python code, enabling interaction with both the device's actuators and sensors, as well as configuring parameters related to image classification. The system captures images using the device's camera, which are processed using the OpenCV library [9].

OpenCV provides functionality for converting captured images into input vectors for neural networks by transforming them into matrices with values between 0 and 255. These matrices are then converted into binary vectors using Python's flatten function.

Interaction with Students - The Frankie platform allows students to customize various aspects of the WiSARD Neural Network, including the number of tuple addresses, neurons in the Discriminator, and the resolution of the images for classification. Robotic parameters like motor speed and ultrasonic sensor distance can also be adjusted to optimize interactions between the robot and its environment.

Students access Frankie's control interface remotely via VNC Viewer, allowing them to adjust system settings on the Raspberry Pi. The terminal interface provides a range of customizable variables, enabling students to explore both robotics and AI in tandem.

The code allows configuration of key parameters like the optimal distance for object classification, motor speed, retina dimensions for image processing, the number of tuple elements (which define memory allocation for neurons), and the "Trust" variable, which indicates the classification confidence.

The main interactions with the platform are:

- The determination of the optimal distance between the image to be classified and the robotic device.
- The adjustment of engine speed and duration of movement.
- The specification of the dimensions of the retina, given its square configuration.
- The selection of the number of elements in the tuple, which dictates the number of memory addresses allocated to each neuron.

- The definition of “Trust,” which quantifies the percentage of confidence that the classified label corresponds to the trained image.
- The parameters, configured by default in the code, facilitate the training of four distinct classes of labels. For example, Class 1 - triangle; Class 2 - square; Class 3 - circle; and Class 4 – star (Fig. 4).

During workshop activities, students produced black images on white paper and had the opportunity to create additional images for the training phase, followed by subsequent classification tasks.

Upon classification, each image was associated with specific actions for the robotic device. For instance, if the code identified an image as a triangle, the robot would advance forward. In contrast, if a square was classified, the robot would execute a right turn. Similarly, a classification of a circle would prompt the robot to turn left, while identifying a star would cause the robot to move backward.

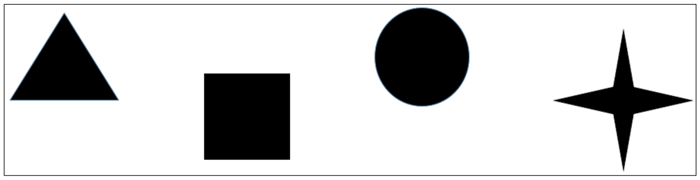

Figure 4. WiSARD Trained Images

Students had the flexibility to modify the definitions of the trained labels and the corresponding actions of the robotic device based on the results of the label classification.

Additionally, the code was configured to display an error message if none of the predefined images were detected. Students could also set the accuracy threshold for image identification, allowing the robot to accept an image as a match if it meets the specified confidence level.

Challenges in Implementing the Code - One of the main challenges during the project was interpreting images captured by the webcam. The proximity of objects to the camera affected their size, meaning an object closer to the camera appeared larger than one further away. Additionally, different object positions led to varying interpretation results. For example, a single image in the camera frame could yield different outcomes depending on its distance and position.

To address this challenge OpenCV library resources were utilized, particularly the *findContours* function, which detects white shapes on a black background. In the Frankie system, this function isolated geometric shapes from the binarized and inverted image captured by the robot. The cropped image was then resized to standard dimensions, ensuring uniformity regardless of the object's distance from the camera.

After resizing, the image was inverted again before being processed by the WiSARD algorithm. These steps allowed the code to consistently work with a standard-sized image, and positioning was stabilized by defining a square around the shape.

However, two issues persisted. First, if the image was outside the camera frame, it could not be recognized. Second, low-contrast images posed challenges since they could be interpreted as white. The first issue can be resolved by training the WiSARD algorithm to recognize partial images, though this was not implemented. The second challenge, with light images, can be addressed through dynamic thresholding, adjusting the threshold during binarization to improve contrast detection.

3 METHODOLOGY

The research adopted an exploratory and descriptive case study approach, which allowed an in-depth analysis of the processes involved in teaching AI concepts to adolescents. The focus was not only on evaluating knowledge acquisition but also on understanding the social and interactive dimensions of the learning process. Eleven students between 14 and 16 years old participated in the study. They were part of a tuition-free high school residency program in Rio de Janeiro, consisting of 3 girls and 8 boys, all without prior knowledge of machine learning or programming. This context was essential, since the project aimed to evaluate the feasibility of teaching AI to students starting from a basic mathematical foundation.

The methodology was guided by Vygotsky's learning theory, particularly the concept of the Zone of Proximal Development (ZPD) [10]. Structured activities were designed to help students move from their actual development level (knowledge they could use independently, such as simple arithmetic and recognition of binary representations) toward potential development, achieved with mediation and peer collaboration. The workshops were structured into five stages, conducted over seven sessions (10.5 hours total). Each workshop focused on specific objectives: understanding the WiSARD model through unplugged exercises; programming and image classification in Google Colab; working with datasets and OpenCV; interacting with the Frankie robot; and configuring the robot to carry out classification tasks in real-world conditions.

Multiple strategies for data collection were adopted to ensure reliability and richness of analysis. These included scripted activities (both written and digital), a researcher's field diary, video recordings of the workshops, and direct observation of the robot's functioning under student control. The triangulation of these sources allowed a multidimensional interpretation of the students' learning path. In addition, the robotic code configurations provided an objective way to assess student progress, since classification accuracy and trust values directly reflected the students' ability to manipulate WiSARD parameters.

The Frankie robotic platform played a central role in the methodology. Built with a Raspberry Pi and low-cost sensors, Frankie enabled direct interaction between students and AI processes. Students could configure image classification parameters, control robot movement, and experiment with decision-making processes derived from the trained neural network. The integration of video lessons (via Edpuzzle), unplugged mathematical activities, collaborative programming in Google Colab, and hands-on robotic interaction created a diversified methodology that addressed different learning styles and progressively increased complexity. Ethical approval was granted by the Brazilian National Ethics Committee, ensuring adherence to research standards and protection of participants' rights.

The workshops developed using the Frankie Platform were carefully designed to engage students as active participants in their learning process. The resources and activities integrated into the workshops were as follows:

- Interactive Video Classes: Video classes were employed as an educational tool across various contexts. To teach the Weightless Neural Network (WNN) WiSARD, an interactive video lesson was utilized through the Edpuzzle platform. Edpuzzle fosters active learning by allowing students to engage with content through interactions such as video segmentation, voice-recorded commentary, and embedded assessments, which can be accessed by educators to track student progress.
- Unplugged Activities: These were designed to introduce main concepts of the WiSARD WNN without requiring the use of computers. They allowed students to understand abstract concepts through hands-on activities.
- Google Colab Collaboration Platform: Google Colaboratory (Colab) is a cloud-based platform based on Jupyter Notebook, enabling collaborative teaching and research in Machine Learning. Similar to Google Docs, Colab allows users to share and co-edit notebooks, and supports Python 2 and 3. It also provides native libraries such as OpenCV for computer vision, as well as tools for Artificial Intelligence and Machine Learning like TensorFlow and Matplotlib.
- Native Codes: Python was the programming language used in the activities. No prior programming experience was required, as codes were provided via the workshop's website, http://bit.ly/FrankieLabZero. Three main "Native Codes" were utilized:

- Native Code 1, developed by Lima Filho et al. [11], available on GitHub, is a Python version of the WiSARD library used for training and classifying labels based on binary vectors.
- Native Code 2 builds on the first code, adding functions for image processing and converting images into binary vectors using OpenCV.
- Native Code 3 links Native Code 2 to the robotic components of the Frankie device, enabling its operation in the environment.

Skills and Competencies aimed to be covered in the Workshops - The workshops aimed to equip students with the competencies necessary to configure the WiSARD WNN embedded in the Frankie Platform, particularly to optimize the Trust percentage when classifying images. The content covered in the workshops included the following key concepts:

- Retina Definition: Understanding the structure and purpose of the retina in WiSARD.
- Pixel Count in the Retina: Learning the importance of pixel numbers in image classification.
- Binary Image Representation on the Retina: How binary images are represented for processing.
- Transformation of Binary Matrix into Input Vector: Converting binary matrices into input vectors for classification.
- Tuples as Ordered Sequences: Understanding how retinal elements are organized into tuples.
- Random Tuple Selection: The randomness involved in selecting tuple elements.
- Neurons as Random Access Memory (RAM): Understanding how neurons function within WiSARD.
- Memory Locations: The significance of memory locations in neurons.
- Tuple Element Count and Memory Addresses: Exploring the relationship between tuple elements and memory addresses.
- Discriminator and Neuron Count (RAM Nodes): Understanding how discriminators classify patterns based on the number of RAM nodes.
- WiSARD Training: How the WiSARD neural network is trained to recognize patterns.
- Classification and Generalization: How classification and generalization are achieved through RAM nodes.
- Trust in Classification: Understanding and optimizing the Trust percentage during classification.

4 RESULTS

The results demonstrated that the methodology successfully promoted students' understanding of both theoretical and practical aspects of AI.

In Workshop 1, students grasped basic concepts of the WiSARD model, such as the role of the retina, tuples, neurons, and discriminators. Although some encountered difficulties in associating tuple elements with neurons, they overcame these with teacher mediation. A remarkable outcome was that several students independently derived a formula to calculate the number of neurons, showing a level of reasoning that surpassed initial expectations.

Workshop 2 introduced programming in Google Colab. Despite their lack of previous experience with Python, students were able to execute codes for training and classification. Errors such as indentation problems were common at first but gradually resolved with peer support. Students connected concepts from the unplugged activities to the automated computational processes, reinforcing their learning. By the end of this workshop, all students had managed to program WiSARD to classify images with acceptable trust values.

Workshop 3 deepened this process by integrating the OpenCV library for image processing. Students created their own datasets by drawing geometric figures, photographing them, and processing the images into binary vectors. They recognized that OpenCV automated procedures they had previously done manually, and many noted that increasing the number of training images improved classification accuracy. This step marked a consolidation of their ability to link theory with practice.

Workshop 4 was the first contact with the Frankie robot. Students used remote access to configure and control the robot, associating WiSARD classifications with robotic movements (forward, backward, right, and left). This stage proved highly motivating, as students perceived the direct application of abstract concepts into tangible actions. Some even suggested improvements to the robot's physical design, showing a sense of ownership and engagement.

Workshop 5 brought together all previously developed skills. Students expanded datasets, optimized WiSARD parameters, and adjusted robotic configurations to perform classification tasks in real-world conditions. Practical field activities showed that students were able to control the robot effectively and refine trust percentages through systematic adjustments. Performance was assessed using four levels (Not Achieved, Partially Achieved, Achieved, Fully Achieved), and results indicated that most objectives were achieved or fully achieved across the group.

A self-perception questionnaire using a Likert scale confirmed these findings. Students expressed that the Frankie project facilitated their engagement with AI concepts and that the combination of mathematical reasoning, coding, and robotics was both accessible and motivating. While some reported initial difficulties with code modification and dataset creation, most agreed that the learning process became progressively easier. Importantly, students also raised ethical questions, such as the risk of unemployment due to automation, the potential for corruption of AI systems, and the responsibility of developers in protecting data. These reflections highlight that the project stimulated not only technical knowledge but also critical thinking about the societal impacts of AI.

5 CONCLUSION

The case study confirmed the viability of introducing AI concepts in high school education through the integration of machine learning based on a weightless neural network, mathematics, and educational robotics. The step-by-step methodology allowed students with no prior knowledge to progressively master increasingly complex tasks, from simple binary representations to the implementation of a functional robotic prototype capable of making autonomous decisions based on learned patterns. The pedagogical design grounded in Vygotsky's theory proved effective in creating Zones of Proximal Development that supported active and collaborative learning.

The results also showed that the Frankie robot played a key motivational role acted not only as a tool but also as a learning partner that encouraged students to work together and in a creative way. Students cultivated a sense of empathy for the robot, aiming to achieve accurate results, highlighting the emotional aspect of learning. This involvement illustrates that hands-on, interactive tools can greatly boost enthusiasm for STEM fields and cutting-edge technologies such as AI.

From a broader perspective, the study contributes to filling a research gap in AI education, particularly regarding the teaching of Weightless Neural Networks in schools. While most robotics-based educational projects focus on programming and basic engineering skills, this research demonstrates that it is possible to teach more advanced AI concepts in an accessible and meaningful way. By linking mathematics, computer science, and robotics, students were not only able to understand how algorithms function but also to critically reflect on their applications and ethical consequences.

In conclusion, the integration of the Frankie platform and WiSARD neural network into structured workshops provided a comprehensive educational experience. The findings suggest that similar approaches could be scaled to other schools, fostering AI literacy among younger generations. The combination of unplugged exercises, collaborative coding, and robotic experimentation represents a promising pathway for preparing students to engage thoughtfully and responsibly with AI technologies in the future.

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