An Active Tangible User Interface Framework for Teaching and Learning Artificial Intelligence

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ABSTRACT
Interactive and tangible computing platforms have garnered increased interest in the pursuit of embedding active learning pedagogies within curricula through educational technologies. Whilst Tangible User Interface (TUI) systems have successfully been developed to edutain children in various research, TUI architectures have seen limited deployment in more complex and abstract domains. In light of these limitations, this paper proposes an active TUI framework that addresses the challenges experienced in teaching and learning artificial intelligence (AI) within higher educational institutions. The proposal extends an aptly designed tabletop TUI architecture with the novel interactive paradigm of active tangible manipulatives to provide a more engaging and effective user interaction. The paper describes the deployment of the proposed TUI framework within an undergraduate laboratory session to aid in the teaching and learning of artificial neural networks. The experiment is assessed against currently adopted educational computer software and the obtained results highlight the potential of the proposed TUI framework to augment students' gain in knowledge and understanding of abstracted threshold concepts in higher education.

Author Keywords
Tangible User Interface; Computer-aided instruction; Higher Education; Artificial Neural Networks.

ACM Classification Keywords
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INTRODUCTION
Through the rapid evolution of technology, emerging interaction techniques have provided the educational domain with new and smarter possibilities to support cognitive learning processes [28]. This evolution has brought with it a higher standard of intuition which necessitates users to exert less effort to make use of computer systems [34]. Thus led technology to new interaction paradigms of touchscreens, gesture recognition devices and tangible interfaces which are slowly replacing the conventional computing peripherals such as mice, keyboards and controllers [23].

As educators seek to engage evermore in active learning concepts and constructive-based solutions instead of the traditional exposition-based teaching methods that follow a "teaching-by-telling" methodologies [38], interest in educational technology has augmented as a promising means to enable modes of autonomous learning [39]. The introduction of such novel and smarter interaction technologies within the educational industry has been supported by multiple academic researchers so to provide an enhanced and enriched teaching and learning experience [3,42].

In particular, TUI systems provide an uniqly intuitaive user paradigm for students which operate through physical manipulation natively interlaced digital data representations [19]. This concept improves the interaction domain between human and computing machines by enabling users of TUI systems to take advantage of innate spatial and environmental skills [29], whilst interacting with and configuring physical objects [33]. Moreover, substituting real-life familiar objects instead of digital controlling options enables TUI systems to increase an application's intuitiveness which eases out the understanding of the concepts explained.

The introduction of Tangible User Interfaces (TUIs) as an educational technology quickly received interest in such a context especially for its effectiveness towards augmenting student motivation [6]. Following a comparative study with Graphical User Interfaces (GUIs) on creative design processes, the interaction techniques provided by TUI architectures outlined a substantial enhancement in student's design abilities as well a reduction of the cognitive load needed to interact with the technology [12].

Alternate studies further concluded that graspable/tangible user interfaces provide better retention of knowledge amongst students in educational applications [3] and are remarked as instruments that help learners in areas of; "development, sensory engagement, accessibility, collaborative activities and understanding of the world around them" [45].

The usefulness of TUIs for augmenting user's ability in problem-solving environments was also outlined by [32], which proposes a generic intelligent TUI system, 'Combinatorix', which allows students to explore and learn problem-solving techniques by manipulating physical objects and exposing potential solutions. The evaluation of this study showed that by aiding to picture all possible options to a given problem, the TUI system resulted in reduced cognitive stress amongst the evaluated students [32]. Similarly, 'AstroGrasp' was created to facilitate learning on astronomy concepts which allows students to interact with physical representations of the Earth and Moon, whilst observing representation of rays and shadows [1].

'Augmented Chemistry' embedded the TUI concept with augmented reality to allow students to inspect and interact and visualize imported molecular compounds from an extensive scientific database [4]. These enhancements in tangible manipulation and visualization were also corroborated in the study by [15] which developed a TUI which to aid explaining thermal transfer between objects. This was achieved by heating up an experimental material, whilst thermocouples monitored the heat transfer, which was subsequently displayed on the explainable tangible user interface provided.

Apart from these bespoke implementations in advanced education, the potential of this technology was mainly investigated in the primary educational domain. Examples like 'BrainExplorer' provide an insight into the effectiveness of engaging users is more creative ways via "interactive storytelling systems" [40], that seek to eliminate the use of textbooks whilst providing a hands-on experience. Authors in [31] further attest that such the smarter paradigms provided via TUI systems help students more effectively in tasks such as "memorizing scientific terminology, understanding a dynamic system, and transferring knowledge to a new situation".

Yet, whilst integration of these learning benefits together with the inherent attractive and eye-catching aspects of TUI systems [14] led to positive results when integrated within younger learning environments, the technology has so far lacked equal successful application within higher educational institutions (HEIs). This peculiar domain provides a number of unique challenges with respect to the adoption of effective and intelligent educational systems to help students overcome their "concrete operational phase" when learning new concepts [43]. Thus, this requirement necessitates TUI technology to aptly mitigate the challenges faced in engaging a mature audience with concepts of higher orders of complexity and abstraction from concrete experiences [27].

In contrast to the implementations in literature, this paper introduces a novel interaction concept within TUI frameworks by augmenting interactive surface architectures with active tangible manipulatives. This unique interactive paradigm presents TUI architectures with a smarter way to engage users and intelligently influence their scope of interaction. To further the limited successes identified in the literature on the of the efficacy of tangible systems in higher education, the proposed TUI architecture will be investigated for its ability to aid in the teaching and learning of abstracted Artificial Intelligence (AI) concepts such as Artificial Neural Networks (ANNs). The paper is organized so that a review of computer-aided techniques used to educate ANNs is presented in Section II. Section III outlines the proposed smart interactions within an adapted TUI architecture from both a tangible and digital perspective. The obtained results from deploying the system within a university programme are presented and discussed in Section IV. Finally, the last section outlines a brief conclusion of the presented work and the suitability aspects to this smart tangible computing in education.

ARTIFICIAL NEURAL NETWORKS

Within the domain of computer science, ANNs have quickly gained popularity as highly versatile machine learning algorithms with applicability in a myriad of applications ranging from image processing to autonomous control [18]. Defined by [11] as; "a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs", this AI algorithm is further strengthened by feedback techniques such as back-propagation that provide a semi-supervised learning approach to optimize an output function convergence [7].

The ability of ANNs to address problems in classification, regression, time-series forecasting and complex system modeling [2] has consequently made the tuition of this machine learning (MLA) algorithm a stable within computer science and engineering degree programmes [13]. Yet, despite its widespread adoption, the complex nature of the ANN algorithmic processes poses a common difficulty to teaching within HEI contexts, thus leading academics to often rely on application software packages to aid in their educational delivery [30].

Amongst the most popular environments in use for this purpose are the Waikato Environment for Knowledge Analysis (WEKA) and MATLAB™, which allow students to process real datasets whilst making use of prebuilt libraries and toolboxes [13,16]. Both platforms provide user's the ability to preprocess, classify, cluster, associate, visualize and select attributes for given data. However, albeit these tools allow students to analyze the results of

ANNs, their use is often overwhelming for inexperienced users and often hinders the student's abilities deeply learn the algorithmic processes.

Addressing the visualization limitations above is commonly achieved through using bespoke educational software for ANNs. Applications such as TensorFlow allow students to interact with simulators online to allow customization of neural network architectures and visualize the obtained results [37]. Similarly, the Sharky Neural Network application adopts animation aspects to introduce students to simulated process and adaptably visualize the obtained results [35]. Whilst contributing to the visualization aspects of teaching and learning ANNs, these packages however often lack technical flexibility . This limits the ability for students to experiment with operational parameters in order to conceptualize their understanding [26].

More adaptable platforms such as Scikit-Learning [8] and Theano [41] allow students to easily set up and customize neural networks by making use of implementation libraries. Packages such as Pylearn2 [17] and Pyevolve [9] further extend ANNs with other MLAs, such as genetic algorithms, to extract further analysis from the obtained data. Comparably, the Caffe package facilitates the adoption of ANNs in image datasets and allows for the development of neural network architectures for detecting and classifying objects within images [20]. The technical capabilities of these applications however often technically overburden students with significant coding requirements and thus limits their ability to properly comprehend the underlying concepts of the ANN algorithmic process.

To this end, learns often resort to audiovisual media for studying the complex operational details of such algorithms, seeking educational channels on YouTube and virtual learning platforms to provide explanations and video-led examples [24]. Nevertheless, the sole use of diagrammatic representations and narration to explain the ANNs concepts, is functionally tantamount to the traditional lecturing approaches adopted within HEIs, which active learning pedagogies aimed to explicitly replace and augment using more engaging approaches.

PROPOSED ACTIVE TUI FRAMEWORK

In light of the above limitations to adopt educational technologies in this fundamental AI technique, this paper provides a contribution to enhance the teaching and learning of abstract concepts, such as those present in ANNs, using a real-time interactive educational tangible platform. Furthermore, in distinction from the current literature on TUI systems, this research proposes a novel interaction paradigm achieved by adopting active tangible manipulatives on an interactive surface architecture. This smarter technology is developed to aid mitigate the peculiar and augmented conceptual complexity experienced within HEI environments.

Physical Overview

The architectural system model proposed by this active TUI framework is that of an interactive tabletop design augmented with tangible computing. Based loosely on the MCRpd model proposed by [19], the proposal extends the interaction and feedback methodologies of TUI systems by integrating active microprocessor-controlled objects with a tabletop configuration. This design was conceived to enable the provision of additional manipulation capabilities which aid in the representation of abstracted educational concepts such as ANNs to HEI students.

Considerations in hardware design were also undertaken to account for the peculiar nature of HEI which intrinsically caters for different student demographics. The advanced complexity levels of ANN process necessitated the need to various simultaneous visualizations and interactions to be undertaken hence needing larger interactive surface area than conventional tabletop systems. This was mitigated by designing a $1.3m^2$ interactive surface area tabletop whilst constraining the overall height dimensions to 90cm so as to retain comfortable reach and interaction by adult HEI students as detailed in [25]. These scaled architectural dimensions aided to engage larger numbers of students in collaborative interaction whilst accommodating for the comfortable visual and interaction dimensions of average-height HEI students.

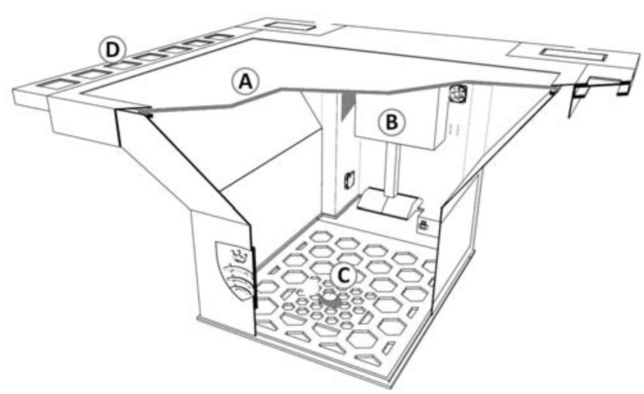

Figure 1. Construction cross-section of the proposed TUI:
a) Tabletop interactive surface,
b) Short-throw projector,
c) Wide-angle CCD camera with IR band-filter,
d) Side trays with illuminated TUI placeholders

As depicted in Figure 1, these design constrictions were addressed by making use of a short-throw projector mounted underneath a semi-transparent surface. The latter, made from an acrylic panel, was chosen due to its ability to clearly capture the projected image whilst allowing tangible objects to be seen from underneath. A wide-angle camera was employed to capture the surface area and provide visual feedback to the system. In tandem with the reacTIVision framework [21], the setup allows the conversion of tangible manipulation into digital control of the TUI software.

The active aspects of the proposed TUI system were designed using a distributed embedded microprocessor architecture. Adjacent to the table two tangible placeholder shelves were designed, as shown in Figure 1d, with integrated individually-controlled RGB lighting for each unique placeholder. This further enabled the system to direct students on appropriate use of TUI elements in a non-coercive approach.

Active Tangible Interaction

The proposed TUI framework presents an innovative interactive engagement paradigm to students by yielding an additional domain of user interaction through a set of active 3D physical objects. These objects were adapted by the TUI framework to allow the real-time design and configuration of neural network topologies as well as their operational parameters. The altering of these digital parameters using physical manipulatives is a central concept to TUI systems and hence a fundamental objective was to provide students with a heightened sense of intuitiveness and familiarity with tangible objects, thus reducing the barriers of interactivity commonly experienced by mature HEI students.

The active tangible concept was developed by embedding tangibles with autonomous computational architectural units that communicate wirelessly with a central processing server. To this end, within the base of each tangible object, an Arduino Nano™ was integrated, together with a small LiPo battery and a Bluetooth® communication module. This bi-directional communication architecture enabled each tangible object to independently transmit and receive data from the server processor via a serial communication protocol. To enable the optical recognition of objects by the computer-vision toolkit, a unique 'amoeba' marker [5] was attached underneath each object. This provided the framework the capability to passively track and intelligently control active components within tangibles. Furthermore, this approach introduced real-time multichannel user feedback through passive computer-vision and active tactile/analog interaction.

To aid in the teaching and learning process of ANN concepts, a 'horse-racing analysis' contextual example was adopted to explain the artificial intelligence algorithm. This context simulated the relational model of horse race time based on parametrical data of speed and health. The selection of this domain exploited the inherent familiarization and prior exposure of HEI students with the typical data of this application domain, hence perceptively reducing the cognitive load experienced by students whilst interacting with the novel framework. The aesthetic design and functionality of tangible objects were subsequently further adopted to symbolize and represent different ANN parameters ranging from input, hidden and output nodes as well as network parameters and configuration adapters. As pictured in Figure 2, these neural network concepts are innately expressed by the tangible objects within the 'horse-racing' context in an instinctively recognizable manner.

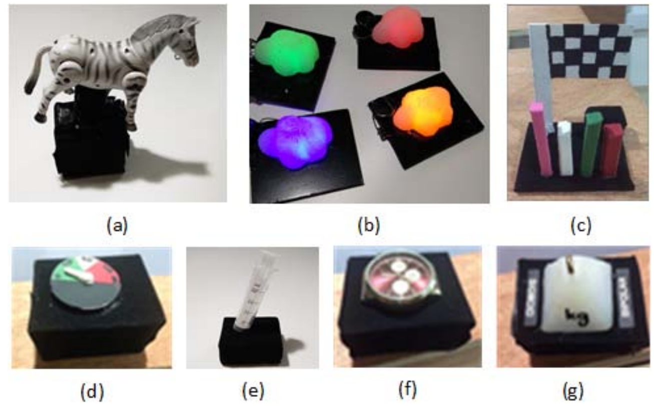

Figure 2. Active tangible objects contextualized for ANN operations including;
a) Horse - Context Simulator Controller,
b) Clouds – Hidden Layer nodes,
c) Finish Podium – Output Visualization,
d) Speedometer – Input Speed Value,
e) Syringe – Input Health Value,
f) Chronograph – Output Time Value,
g) Weight – Synapse Weight Adjustment.

Through embedded interaction with digital and physical feedback, these devices provided the TUI framework with the ability to computationally couple physical manipulations with ANN operands. These interactions are further elucidated in the following systematical descriptions:

- Horse Simulator Controller (Figure 2a) – The horse tangible represents the contextual data scenario and consequently triggers the loading of the appropriate dataset on the neural network AI algorithm. Students dynamically use this tangible to alter between setup and configuration modes of the designed ANN using positional shifting of the manipulative. Rotating the tangible at any stage in execution mode further controls and alters the training rate of the algorithm. This configuration interaction hence allows students to visualize and understand the training and convergence process in different modes of speed. The dynamic interaction is further communicated to the user via actively controlled feedback which via embedded actuators animates the figurines legs to simulate a functional galloping action whose pace is directly mapped with the ANN training rate.
- Cloud Nodes (Figure 2b) – A set of active cloud nodes were used to represent the abstruse nature of hidden layer nodes in ANN. Hence, by dynamically adding or removing these abstracted nodes, students were enabled to design and visualize the behavioural effects of differently configured topologies. The active tangibles were composed of translucent polylactide (PLA) material into which an actively controlled Light-Emitting-Diode (LED) was embedded. This intelligent interface aided student engagement by providing a color-coded relational

representation of output synapses. In addition, pervasive feedback interaction is used during the convergence process to intelligently engage student attention towards computational executions by timely triggered light strobes from the tangible.

- Result Podium (Figure 2c) – This finish line tangible embedded the representation of output results computed after each ANN iteration. By rotating the tangible, students can alter the result visualization of either the tabulated output values or a graphical representation of the estimated percentage error fed back though each back-propagation epoch.
- Speedometer (Figure 2d) – This active input tangible was designed to represent the variable speed of the simulated racing-horse input data. Via rotational interactions, students could alter the nodes input value which would be interactively reflected visually in both a displayed digital value as well as through proportionate dynamic analogue servo movement of the physical speedometer's hand.
- Syringe (Figure 2e) – The second input parameter was altered by users through the physical use of a syringe. This active tangible allowed students to alter the horse health data value which was exemplified as an input parameter to the ANN topology.
- Chronograph (Figure 2f) – This tangible output representation provided students the ability to toggle through testing or training simulation modes on the network. By actively engaging with the tangible through positional and rotational interactions, students can provide the ANN with an expected output data value, which would allow students to visualize the convergence process of the neural network to the newly trained outcome. Alternatively, the removal of this object indicated algorithmic testing conditions where the ANN needed to derive the output data.
- Weight Adjustment (Figure 2g) – This active TUI tangible was designed to allow students to experimentally learn and interact with the ANN operations. The translucent weight symbol, allowed students to select and configure internal ANN synapses by tangibly engaging with their parameters. By dynamically altering the RGB light from an embedded LED, the TUI framework provided intelligent feedback to users by changing its internal color to match that of the linked synapse. This mitigated the potential graphical clutter of complex topologies by allowing the TUI framework to provide positional assurance to students on the intended selection. Rotational interaction during setup stage also allowed students to configure the synaptic activation function whilst during configuration mode, the interaction would override the synaptic weight value with users input. This data value was further actively related back to students through a relational variation of lighting intensity of the physical tangible's LED.

Digital User Interaction

The proposed TUI framework embedded digital information through an interweaved GUI that provided an intuitive physical interactive experience. In stark contrast to the limitations imposed by Windows, Icons, Menus, Pointers (WIMP) systems, the proposed TUI architecture endowed additional flexibility options that were exploited to augment user immersion and learning processes.

The graphical interface was produced and implemented using Adobe Illustrator and the Unity^{TM} game development environment. The framework behavioural interaction was programmed using C# which allowed the integration of animations based on the tangible information obtained through the TUIO communication protocol [22]. Furthermore, the framework integrated with a developed Python neural network simulator which whilst providing authentic representation of real-time data through functional AI computation also unbounded students in their flexibility to customize and configurate ANNs.

The GUI interface pervasively aids student interaction by providing subtle visual cues which are designed to aid in the experimental learning process and digitally interlink with physical manipulation. The interweaved design elements between visual animations, TUI execution and user interaction of the proposed TUI framework are systematically detailed in this subsection through a review of the framework's operation sequence.

The startup interface, illustrated in Figure 3a, presents students with a sectional layout to aid in the stage design of the ANN. As shown within Figure 3, by suitably embedding visual iconic symbols, students are guided through the TUI interaction through projected cues. These help to instinctively stimulate tangible interaction using appropriate placeholder indication. Once objects are placed on the interactive surface, the TUI framework makes use of digital timers, animated via radial filling as shown in Figure 3c, to allow users to assert their decided actions through physical manipulations. Following the successful registration of user interactions, the framework progressively advances through execution/customization stages, providing students with the ability to personalize the pace at which they progress through their learning process.

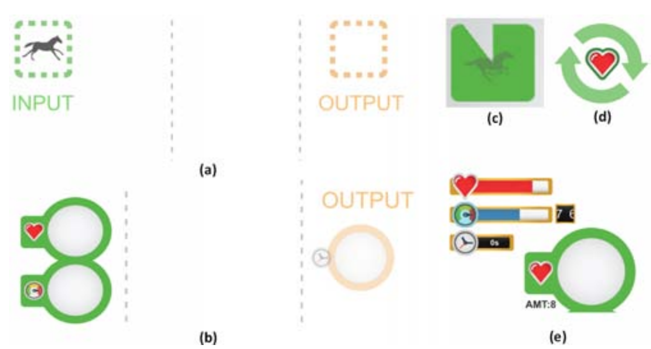

Figure 3. Digital elements designed for pervasive user interaction using the proposed TUI framework.

Subsequent to the loading of the 'horse-racing' dataset, via the 'horse' scenario controller, the TUI framework presents the contextual network's hyperparameters by visualizing the distinct input and output nodes of the ANN as illustrated in Figure 3b. Simultaneously, embedded LEDs actively flash on the respective input tangibles, pervasively diverting the student's attention towards the applicable interactive objects. Visual imagery further this smart interaction by helping students associate the digital/physical computational coupling by using indicative elements as pictured in Figure 3d. By manipulating the appropriate tangible, students are able to customize the input/output parameters for health, speed and time values, thus experimentally designing and configuring their custom simulation. Interactive feedback is provided during this stage by blending the use of pertinent icons, completion bars, and variable value scrolls, as shown in Figure 3e. This customization process is further reinforced within the TUI framework by the physical feedback provided using active actuators and input sensors on tangibles.

The use of proxemic interaction is also embedded within the tangible user interface by allowing students to dynamically configure synaptic links between nodes by placing the respective tangibles in physical proximity. This allows students to freely customize and experiment with ANN topologies augmenting the students' cognitive and learning process through user-centric progressive complex adaptions. To pervasively guide user's interaction, cloud tangibles which at setup stage represent the insertion of hidden nodes, are also interactively animated, by lighting up internally using the embedded LEDs as shown in Figure 4a. Once utilized and connected, color-coded internal synaptic links are projected on these tangible 'hidden' nodes, representing their connected topology as illustrated in Figure 4b.

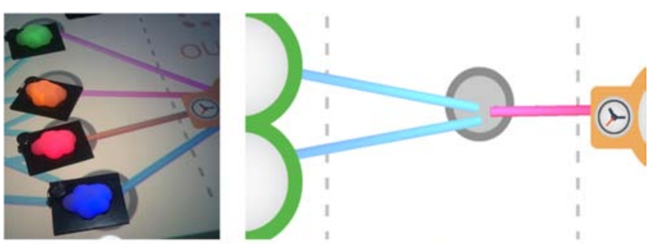

Figure 4. The configuration of hidden nodes and synapses using active cloud tangibles.

Following the connection of the ANN topology, the weight adjustment controller can optionally be utilized to customize the activation function on the synapse. This active tangible object is timely animated to indicate availability to the user. Thus, once placed near a created synaptic link, students can alter the selection of an algorithmic function. Making use of rotational interaction guided via pertinent circular graphics as illustrated in Figure 5, the framework provides students with the ability to experiment with different functional operands, which are visually explained to students using familiar mathematical graphs.

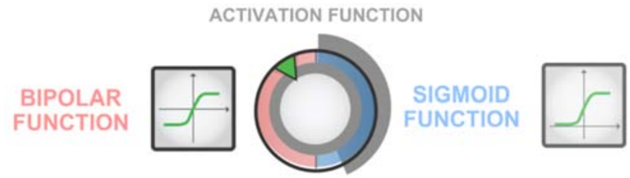

Figure 5. Selection of synapse activation function through rotational interaction and dynamic digital feedback.

Whilst the ANN is being constructed, students are provided with the option to switch between setup and configuration mode led through visual projection of graphics adjacent to the horse controller as shown in Figure 6a. Once the tangible is positionally dragged onto the 'start' placeholder, the input graphical information is summarized for users as shown in Figure 6b, whilst a new set of visual operands is projected near the tangible object. As shown in Figure 6b, these rotational cues provide the user to set the ANN training rate, hence idling or speeding up the simulation as desired. In tandem with this interaction, the TUI framework actively governs the tangible controller to provide real-time interactive feedback by altering the actuated galloping motion of the horse in relational speed to the rotational digital selection.

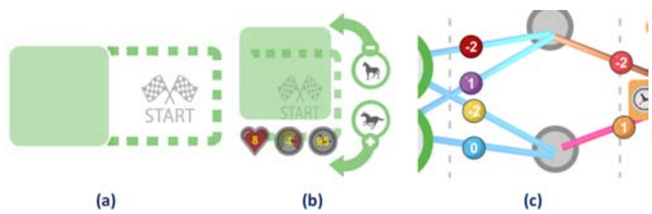

Figure 6. Visual digitization provided by the TUI framework in configuration mode.

At the start of the simulation in configuration mode, synapses are individually assigned random weights as common in most ANN implementations. This visual representation makes use of a suitably designed color-coding scheme, as shown in Figure 6c, to facilitate the student's association of data. To further the experimental learning capabilities imparted by the TUI framework, the proposed implementation multiplexed the use of the 'weight adjustment' object to enable customization of the initial data in configuration mode. The active tangible is therefore illuminated in varying light colors whilst the framework transitions to configuration mode, providing a persuasive indication to users via the physical domain on its potential use. Once placed on the interactive surface, the weight tangible is digitally augmented with a dynamic color wheel, illustrated in Figure 7a, which allows the user to accurately position and select individual synapses. Following the elapse of the interaction timer, the tangible object interactively changes light color to match the lockedin synoptic, indicating to the user the ability to configure specific data values on synapses via rotational interaction and digital visualizations as shown in Figure 7b.

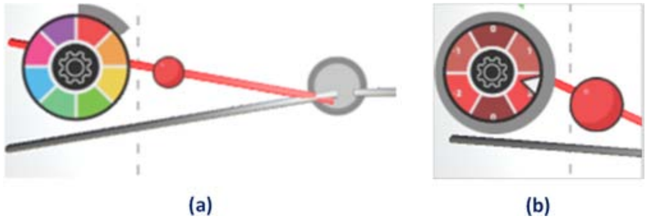

Figure 7. Tangible interaction allowing students to experimentally configure synaptic weight values.

Consequent to the interactive customization of values, the framework aids students understanding the conceptual operation and convergence process of ANN through animated visuals. As shown in Figure 8a, data values are visualized traversing through nodes and synapses whilst appropriate animations are able to explain the mathematical value adjustments as signals propagate through the designed network. These dynamic visualizations provide a more intuitive understanding to the underlying concepts and procedural effects of the algorithm's iterations. Furthermore, at the end of each animated epoch, the underlying ANN scripts compute and display the resultant values of the last few iterations in a tabular graphic projected adjacent to the podium tangible. By physically altering this output tangible, students are further able to graphically interpret the convergence error computed through the last iterations, dynamically monitoring the effects of weight tuning on the algorithms backpropagation adjustments and accuracy.

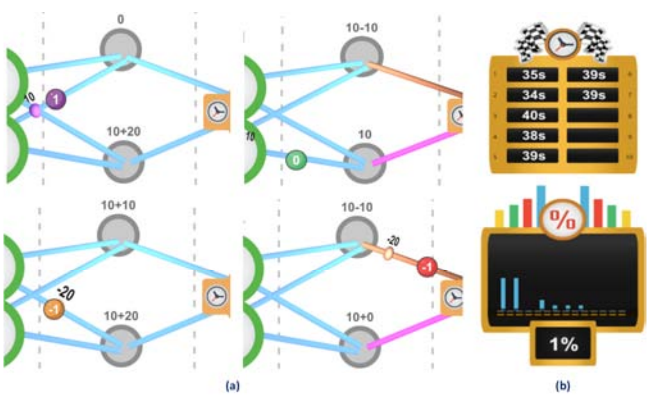

Figure 8. Digital visualizations highlighting internal computations:
a) Animated weight propagation and value calculation,
b) Output result times per iteration together with backpropagated error percentage for convergence.

Once the AI algorithm is sufficiently converged, students are able to further engage with the TUI framework to utilize and understand the developed ANN in predictive AI testing mode. In this mode of execution, the interweaved and perceptually coupled digital and physical domains, as pictured in Figure 9, enable students to self-evaluate the suitability and accurateness of their designed ANN topology by testing its validity on new input datasets. This allows students to individually self-assess their progress and uniquely customize the pace of their learning experience so as to obtain a deeper understanding of the AI concept.

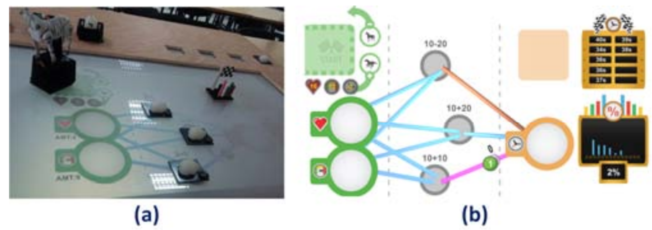

Figure 9. Perceptually and computationally coupled ANN model within; a) the physical domain, and b) the digital domain.

EXPERIMENTAL EVALUATION

The developed TUI framework was deployed for evaluation at Middlesex University Malta within undergraduate degrees in Computer Science and Information Technology. Convenience sampling was undertaken to select 32 students studying the module of Artificial Intelligence who voluntarily offered to participate in the evaluation study. This population sample size was deemed adequate in line with the guidelines in [44]. The undergraduate participants were either in their second or third year of study and varied in age between 18 and 24.

To evaluate the effectiveness of the proposed TUI framework, a direct comparison was undertaken against currently employed PC-based educational technology using a GUI educational simulator. To ensure no additional experimental variables are introduced in the evaluation, a similar GUI software was developed to that created on the TUI framework. As visualized in Figure 10, the educational software was optimized for GUI interaction and usability whilst retaining identical functionality and educational capabilities.

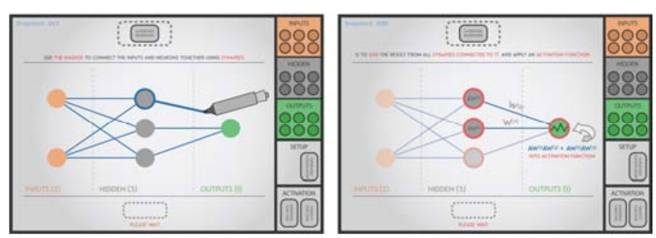

Figure 10. GUI software developed for comparative evaluation.

Artificial neural networks is a foundational topic within the selected course and commonly forms a threshold concept towards the student's progress and understanding of more complex algorithms. Hence, to maximize the evaluation potential of the proposed TUI framework, the experimental sessions were scheduled to coincide with the natural delivery of this topic within the curriculum.

Evaluation Methodology

An evaluation methodology was implemented which was designed to yield a quantitative analysis of the effectiveness and suitability of the proposed TUI framework in HEI contexts. This evaluation data was obtained by using both a usability questionnaire and an open-ended assessment where questions covered both theoretical as well as practical design aspects of ANN concepts. Figure 11 outlines the sequential flow of student evaluation, lecturing and assessment sessions;

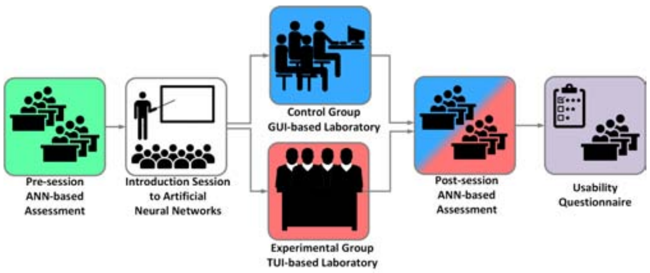

Figure 11. Evaluation stages designed for assessing the suitability of educational technologies for ANN concepts.

To mitigate the potential bias introduced by the students' apriori knowledge of ANN potentially acquired from their related work experience and varied demographics, a differential evaluation methodology was adopted to provide summative assessment on the level of knowledge gain obtained by students [10,36]. To this end, upon commencement all students were provided with a timed pre-session assessment on ANN knowledge. This examination was composed of 12 open-ended questions and covered various aspects of detail and conceptual understanding of the ANN concept. The results obtained from this assessment provided an individualistic knowledge baseline for each student prior to being provided formal tuition on ANN.

Following this initial assessment, students collectively attended a short introductory session. This was delivered in traditional lecture format, whereby basic terminology and foundation principles for neural networks were introduced. This session was delivered by the usual lecturer using the standard lecture slides conventionally adopted for the module to ensure a consistent and appropriate explanation is provided. Subsequent to the lecture delivery, students were randomly split in two equal groups for their laboratory/seminar session on the topic. These cohorts composed the experimental and control groups respectively for the evaluation methodology described. As illustrated in Figure 11 during the laboratory sessions, students sub-grouped in sets of four (4) to solve a number of given group work tasks. The latter were identical to both cohorts and involved the experimental design, construction and analysis of different ANNs topologies within a 'horse-racing' contextual example. The designed variable within the experiment was to enable students within different groups to utilize a different educational technology to undertake and solve the laboratory tasks. Thus, whilst the control group students adopted the traditional GUI-based educational software shown in Figure 10, the experimental group students were able to interact with the proposed TUI adaption pictured in Figure 9.

Following the successful completion of their respective tasks, all students were provided with a usability questionnaire for the respective educational technology utilized as well as a second assessment using similar open-ended questions on ANN concepts. The questions in this examination were designed to assess the various aspects of conceptual understanding including theoretical, detail-focused, procedural and problem-based knowledge as shown in the following questions extract:

- *Why is a Hidden Layer used in an ANN?*
- *How does adding more Hidden Layers affect data?*
- *What happens every time the data passes through Synapse?*
- *Why is the result difference of the Expected Output and Actual Output important?*

These quantitative assessments were designed to provide an evaluation on the knowledge gain obtained by each individual student during the respectively attended session. Equitable analysis on the assessment grades together with the quantified subjective evaluation provided by students in relation to the interactivity and usability of the designed educational technology were able to aid evaluate the respective aptness and efficacy of the proposed TUI framework in HEI contexts.

Results and Discussion

The grades obtained by students within each of the assessment sessions are visually presented in Figure 12. The figure provides a comparative evaluation of the results obtained by students in each distinct question during their pre-session assessment (green) as well as their subsequent post-session assessment following interaction with a GUI-based or TUI-based laboratory session (red or blue respectively). This data was evaluated for each individual student in both educational cohorts using a paired-sample t-test.

Results outlined that students undertaking the control laboratory improved their mark to 39.1% (σ: 15.6) from their initial pre-test score of 15.4% (σ: 3.1). On the other hand, students who engaged with the proposed TUI framework during the experimental setup achieved a post-test average grade of 71.2% (σ: 14.4). Thus, in contrast to the 23.7% (σ: 16.4) knowledge gain obtained during the GUI-based computer laboratory sessions, the proposed TUI framework provided students with a knowledge gain of 55.8% (σ: 13.7) at $p < 0.001$ as shown in the overall comparison in Figure 13.

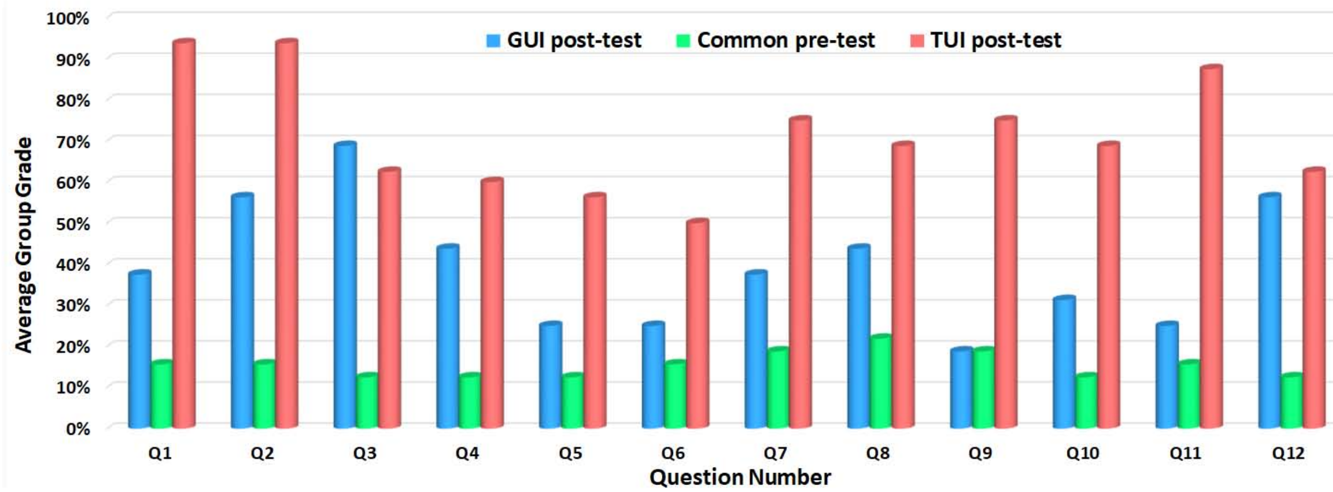

Figure 12: Average grade obtained for each assessed question during the: (left) Post-test of GUI control group, (center) Pre-test undertaken by all students prior to formal tuition on ANN, (right) experimental group after using the proposed TUI framework.

Analyzed under an independent samples t-test, the proposed TUI framework resulted in a knowledge acquiring difference of 32% (σ: 6.1) at $p < 0.001$ with respect to the control student cohort. This difference was directly attributed to the effectiveness of the proposed tangible interactive framework to engage students with abstracted ANN operational concepts. This was achieved in stark contrast to the experimental control group which by adopting a feature-identical GUI setup, illustrated the limited capabilities of the educational technologies adopted conventionally in HEIs.

he remarkable achievements obtained through the TUI interaction were further analyzed to obtain a deeper insight into the teaching and learning capabilities delivered by the framework. The nature of the open-ended questions delivered within assessments were thus segmented according to the different aspects of knowledge evaluated, as shown in Figure 13.

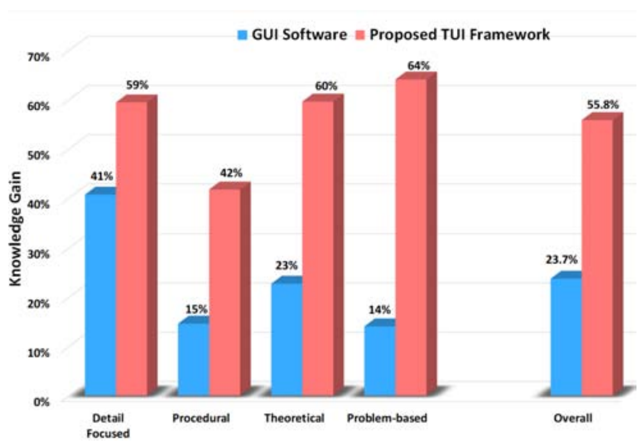

Figure 13. Knowledge gain analyses between educational technologies.

The aggregated results in Figure 13 show that both technologies performed with equitable effectives on 'detail oriented' aspects of knowledge with Q3 in Figure 12 showing a marginal increased ability by GUI software to aid in teaching and learning theoretical definitions. Conversely however, results in Figure 13 immediately highlight the ability of the proposed TUI framework to aid students understand the procedural and theoretical aspects of ANN concepts deeper than that provided by similar GUI software. This can be attributed to the students' ability to tangibly interact with the system's active functionality using instinctive manipulations and feedback channels that augment focus and understanding of the conceptual representations. Furthermore, as outlined by performance difference in answering problem-based questions, the intrinsic capability of the proposed TUI framework to contextualize ANN operation within a familiar environment by using adequately designed tangible representations aids students to assimilate knowledge, thus heightening their ability to apply and understand the underlying abstracted concepts in problem-oriented scenarios.

The aptness of the proposed TUI framework for adoption in HEI was also evaluated using a usability questionnaire that was provided to both groups of students after interacting with their respective educational technology. Using a bi-polar five-level Likert scale, students were asked to quantify their experience in various aspects of their educational pursuit. The subjective usability results presented in Figure 14 outline the effectiveness of the appropriately designed TUI framework to be interacted by users in an intuitive, productive, and ultimately enjoyable manner. Student's feedback demonstrated that albeit the GUI and TUI systems used projected the same information, the information in the TUI framework was perceived to be more effective in understanding and completing the intended ANN tasks.

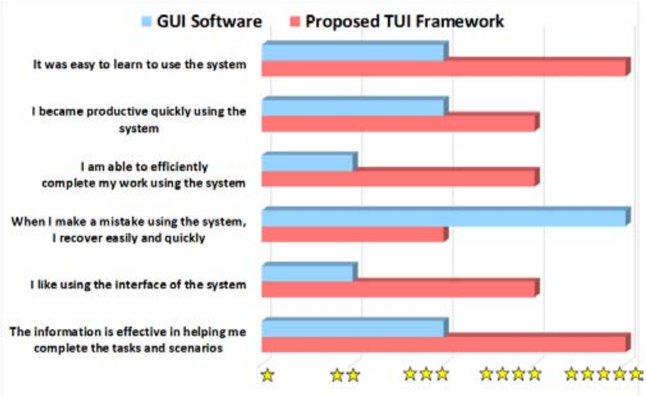

Figure 14. Usability results for both educational technologies.

As shown in Figure 14, a limiting usability factor was conversely noted in the easiness for users to recover the ANN to earlier versions, which when compared to 'back button' deployments in GUI software, the proposed TUI framework necessitated users to redefine parameters and connections by manipulating tangibles accordingly. Nevertheless, questions relating to efficiency in achieving the intended outcome illustrate that students still felt more productive when operating a TUI interface in developing and analyzing different ANN configurations. This statement was confirmed objectively by timing the duration that students took to collaboratively finish their assigned laboratory tasks successfully.

A combined interpretation of results corroborates on the effectiveness of the proposed TUI architecture to interlace the digital information within the tangible domain through a more immersive interface using the novel active tangible interaction paradigm. This reflected on the framework's heightened ability to engage multiple students together whilst facilitate the collaborative learning and engagement on contextual problem-solving scenarios. Whilst the paper described the TUI framework in context of a 'horse-racing' scenario for designing ANN topologies, the observed benefits from adoption of an active TUI framework can be equitably transferred to other AI contexts in light of the described TUI design considerations.

CONCLUSION

The contribution of this paper lies at the confluence of AI education and human-computer interaction. By addressing the limitations of educational technologies in higher educational contexts, this paper proposes an active TUI framework design which is able to cater for the peculiar teaching and learning requirements for abstracted concepts in HEI. Furthering the interactive paradigm of this technology, the described framework actively engages students by interweaving the physical and digital domains of interaction via the novel adoption of active tangible manipulatives on tabletop architectures. Contextualized for teaching and learning ANN algorithms, the proposed TUI framework was deployed in an evaluation process undertaken within an AI undergraduate programme. The experimental and collaborative learning paradigms provided by the tangible architecture led to engaged students achieving an increase in knowledge gain of 32% when experimentally compared to colleagues using traditional GUI software. In tandem with usability evaluation, the paper outlines the aptness and efficacy of embedded TUI frameworks as an educational technology in HEI to help mitigate the challenges encountered when teaching and learning abstract notions.

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