USING AUGMENTED REALITY INTERFACES FOR ARTIFICIAL INTELLIGENCE SYSTEMS

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ABSTRACT

Augmented reality interfaces offer users an effective environment. In this study, a visualization approach with 3D augmented reality interfaces was introduced to enable users to understand and analyze complex deep learning models in a short time. It has been investigated whether the immersive experience that augmented reality creates on the user in other systems has the same effect when analyzing these models. Two-dimensional studies on deep learning models were examined and what could be done in three dimensions was emphasized. By adding another dimension with augmented reality interfaces, a three-dimensional experience is offered to the user and the results are observed. A CNN model is visualized in the application. When test data was given to the model, the feature maps, filters and connections in the layers were displayed. The application was first run in 2 dimensions, then as a desktop application, and then in 3 dimensions, on Microsoft Hololens-2, a mixed reality headset. Tasks are given to users. Usability was measured with a test called the SUM model, which included completion or non-completion situations, errors, completion times and satisfaction. Here, satisfaction was measured using ASQ(After-Scenario Questionnaire), a user satisfaction measurement questionnaire. The usability of augmented reality 3D interfaces was found to be 80%. The conclusion reached with the answers; It has been stated that users are willing to use this system, their awareness in 3 dimensions is undeniable, and these systems can be used as a feature that increases human ability in artificial intelligence systems.

KEYWORDS

Visualization, Deep Learning Models, Augmented Reality Interfaces

1. INTRODUCTION

People can perceive information differently. People can perceive any situation through hearing, touching, seeing, or listening. By using these perception methods together, complexity is reduced when there is an abundance of information. For many people, visualization is the most important of these perception methods. According to Guzman, visualization can be divided into 4 classes. For him, visualization is not only what we perceive with our eyes, but it also includes the psychological aspect of vision. These are isomorphic, homomorphic, analogical, and diagrammatic visualizations [1].

User interfaces enable human-computer interaction and communication. Users can use systems through user interfaces. To design these interfaces for ease of use and to understand users, it is necessary to get to know users, be familiar with their experiences, and design the overall functionality of the system.

From the beginnings of machine learning to the present day, there has been a growing interest in artificial intelligence, which has led to the emergence of deep learning architectures, the most widely used artificial intelligence algorithms today. Many deep learning approaches have been developed to solve artificial intelligence problems along with deep learning architectures. Various industries such as industry, medicine, robotics, image processing, computer vision, object detection, speech processing-recognition, translation, future prediction, and finance are producing intelligent solutions in numerous fields [2].

Deep learning models are created using artificial neural networks. A neural network consists of input values to be trained, and weight values adjusted during training in the hidden layers. After training is complete, the model makes predictions based on new input values. The weights in the hidden layers are updated through the backpropagation method to make better predictions and improve the model's performance. It is important to understand where the model is working as expected and where it is failing by performing these operations. There are many methods that can be used to understand this, and in these methods, inferences are drawn based on evaluation metrics. Visualization is one of the most important methods. Visualizing the metrics in the model makes it easier for the user, i.e., the data scientist, to make inferences while using the model.

User interfaces can be expressed in 2D, or by adding another dimension, they can be represented in 3D. This allows for cognitive, perceptual, and motor performance for people interacting in the physical world. In augmented reality, a 3D representation of the world is created to allow digital objects to coexist with physical objects. Augmented Reality (AR) interfaces enhance the user's perception with additional information by merging parts of the real world with synthetic, computer-generated images [3].

In the second section of this study, we will describe the visualization of deep learning models. In the third section, we will provide general information about augmented reality interfaces. The fourth section will detail our work on visualizing the deep learning model using the Hololens 2 device with the MRTK library. In the fifth section, we will present the results.

1.1. Related Work

When we look at studies that combine augmented reality and artificial intelligence applications, it is evident that they have been used in various fields. In radiology, Trestioreanu et al.[4] combined machine learning algorithms for image segmentation using Microsoft Hololens for use in live medical operating rooms.

Another area where augmented reality (AR) technology is applied is education. Lin and Chen [5] developed a deep learning recommendation system that combines AR technology and learning theories. This system is designed for students with different learning backgrounds and different majors.

Additionally, Bermejo et al.[6] have carried out studies on the combination of big data with augmented reality and their visualization, especially in areas such as tourism, health and public services.

Looking at the visualization of artificial intelligence models; Inkarbekov et al. [7] discusses the exploration of virtual reality as a tool for visualizing AI systems in the context of human-computer interaction. It also highlights the diverse methods within the field of AI visualization, emphasizing the power of interactive 3D visualization and other specialized approaches in making information about AI models more accessible and engaging.

Bock and Schreiber [8] made model visualization in virtual reality using the unreal engine. Yosinski et al. [9] created the Deep Visualization Toolbox based on the development of better tools for visualizing and interpreting neural networks in order to understand how the models work and what calculations they perform in the intermediate layers. It is used to create neuron-by-neuron visualizations using regular optimization.

Kath and Lüers et al. [10] have prepared a virtual reality tool to automate the process of assigning data entries to different categories.

Linse, Alshazly and Martinetz [11] applied visualization in virtual reality by addressing the problem of how to create complex CNNs.

Visualization is of great importance in the implementation of deep learning technologies, which are a subset of artificial intelligence, to facilitate ease of use for the user in data collection, training, setup, and usage. Whether it's monitoring data and models during the application development phase or providing an effective environment for users through augmented reality interfaces in the final application, visualization plays a crucial role in enhancing the user experience.

Many methods are available to visualize deep learning models in 2D for users. Some of these methods use graphical representations when visualizing the model, while others focus on visualizing the network structure. This study has been conducted to answer the question of how augmented reality interfaces will impact users when used to visualize deep learning models. Two-dimensional studies on deep learning models have been examined, and the possibilities of three-dimensional visualization have been explored. Visualization has been achieved through an application using Microsoft Hololens 2, and the benefits of three-dimensional visualization to users has been tested with users working with deep learning models.

The topics we contributed to the literature with this study can be listed as follows:

- We enabled the visualization of the deep learning model on the Hololens device, which is a mixed reality glasses that combines the real environment and the virtual environment.
- We measured the usability of this system by measuring users' perception of 3D interfaces with augmented reality on the Hololens device and 2D interfaces on the monitor.

2. VISUALIZATION OF DEEP LEARNING MODELS ON 2D INTERFACES

Deep learning is a learning approach designed to perform tasks such as creating complex data representations and pattern recognition using multi-layered neural networks. Deep learning is the automatic learning of features by processing large amounts of data and is particularly successful at tasks such as image recognition, text analysis and speech recognition.

A deep learning model is a machine learning model designed to perform complex learning tasks using multi-layered neural network architectures. Such models are particularly successful in tasks that require large datasets and high computational power. The visualization of deep learning models aims to represent the functioning and learning process within complex structures in a more understandable and transparent manner. Deep learning models involve multi-layered neural networks, and these networks perform tasks such as feature extraction and complex data processing.

Deep learning models can be visualized as;

Weight and Activation Maps: Visualizing the weights and activations in each layer of a deep learning model can help you better understand the model's learning process. Heatmaps of weight matrices or activation maps can be used to visualize how the layers are functioning.

Feature Visualization: Visualizing the features learned by the model is actually a method used to understand how the model works on the data and what types of patterns it has learned. Feature visualization reveals how data is represented and processed.

Graphic and Network Structure Visualization Tools: As Graphic Visualization Tools ; TensorBoard, developed for TensorFlow users, is used to visualize deep learning models. It provides information on model performance, learning curves, and graphical representations. Neptune, aims to store, organize, display and compare all metadata created during the model development process. Comet.ml is for researchers and practitioners who want to understand NLP model behavior visually, interactively, and through an extensible tool. Weights and Biases (WandB), focuses on deep learning and allows tracking of training runs with information such as loss, accuracy (learning curves). It also enables the visualization of weight and bias histograms. During training, rich objects like charts, videos, audio, or interactive charts can be logged. Visdom, is a flexible tool for creating, organizing, and sharing visualizations of live, rich data. Hiplot is a straightforward interactive visualization tool that aids AI researchers in discovering correlations and losses in high-dimensional data.

As Network Structure Visualization Tools ; CNNVis, is useful for analyzing a snapshot of a CNN model during training and is focusing on offline analysis. Neural Networks Playground aims to make neural networks more accessible and easier to learn. Neutron is a viewer for neural networks, deep learning, and machine learning models. ANN Visualizer provides visualization by creating a presentable graph of the neural network being constructed.

Qiang Hu, Lei Ma, and Jianjun Zhao, introduced a Pycharm tool called *DeepGraph* that combines visualization and code mapping features to understand and visualize deep learning models[12].

3. VISUALIZATION WITH AUGMENTED REALITY INTERFACES

Augmented Reality (AR) refers to the technology of enriching the real world with digital information. AR adds information generated by computers, such as sound, video, graphics, or GPS data, without obstructing our view and perception of the real environment. This is typically achieved using devices like smartphones, tablets, glasses, or other AR equipment. With Augmented Reality, users can interact with information and other elements that constitute the real environment. Artificial information and objects related to the surroundings can be seamlessly integrated with the real world. AR applications enable users to recognize physical objects in the real world and enhance them with digital content.

Augmented Reality (AR) interfaces refer to graphical or user interfaces that assist users in interactively experiencing the real world and AR content. AR interfaces enable users to interact between the physical world and digital content. Some common examples of AR interfaces include:

Motion Detection and Tracking: AR applications can enable users to interact with objects in the real world by detecting and tracking their movements. This goes beyond simply interacting with touch screens or the physical world, offering a higher level of interaction.

Image Recognition: Users can use the cameras on AR applications to view real-world objects. The application can recognize these objects and overlay digital content on them. For example, during a museum visit, when you view paintings or sculptures, an AR application can recognize these works and display additional information on the screen.

Voice Commands: AR interfaces provide users with the ability to interact with voice commands. Users can perform specific tasks by giving commands to AR devices. For example, you can use voice commands with AR glasses to review a restaurant's menu.

Touch Screens: Touch screens, commonly used in portable devices and tablets, allow users to interact with digital AR objects by tapping and dragging.

Holograms and Virtual World Layers: AR devices can create holographic images or virtual world layers combined with the real world. This allows users to overlay digital information onto or around real-world objects.

Head-Mounted Displays (HMDs): Head-mounted displays for AR provide users with interactive access to AR content in the real world. Examples include Microsoft HoloLens and Google Glass.

Real-Time Data Display: AR allows users to view real-time data by integrating it with the real world. For example, an AR weather application can overlay real-time weather conditions onto the scene the user is viewing.

AR interfaces represent a continuously evolving field aimed at enhancing the user experience and providing more interactions. They create a seamless bridge between the real world and the digital world for users. These technologies are used in many areas, ranging from education to gaming, healthcare services to marketing.

When using augmented reality interfaces, it's important to ensure that these interfaces are user-friendly for the comfort of users. For this purpose, user experience is crucial. User experience (UX) refers to the experience a user has while interacting with a product or service throughout the process. A good user experience helps users achieve their goals quickly and easily, interact with a user-friendly interface, and overall have a positive experience. User-centered designs are required.

4. VISUALIZATION DEEP LEARNING MODELS WITH AUGMENTED REALITY INTERFACES

As a result of the conducted analyses, it has been decided that visualizing deep learning models greatly contributes to understanding the model. In this context, the aim is to provide an immersive environment to the user through augmented reality by presenting a three-dimensional interface. It has been deliberated whether this visualization should be graphical or based on the network structure, and the decision has been made to visualize the network structure. The study has been conducted in this direction.

For the network structure, it is essential to first extract the architecture of the network. This architectural structure was investigated, and it was observed that the study can be divided into

two separate sections: model design and model training. Model design includes the number of hidden layers, activation functions, weight determination, and dropout parameters. Model training encompasses the learning rate, optimization algorithm, epoch, and batch size.

The question to be explored is, "What is the difference in two or three dimensions regarding the benefits of creating awareness for users of the system using these parameters?"

This study is a mixed reality application and will be showcased on the Microsoft HoloLens 2 device.

Microsoft HoloLens-2

The HoloLens-2 device developed by Microsoft combines the virtual and real worlds. It is a wearable headset that allows users to enrich the real world with digital information, providing them with a mixed reality experience. It offers wireless functionality for user convenience. With the help of its sensors, it can track hand and eye movements, and it is capable of accepting voice commands. HoloLens is widely used in visualization applications and research. By merging the real world with digital information, it offers opportunities to visualize data and improve business processes. It is particularly beneficial in the fields of education, medicine, construction, military applications, and industrial use.

4.1. Stages of the Work

In the study, a path was followed as shown in Figure 1. First, a txt file was created to obtain the model's information, and this file was provided to the Unity application to visualize the model.
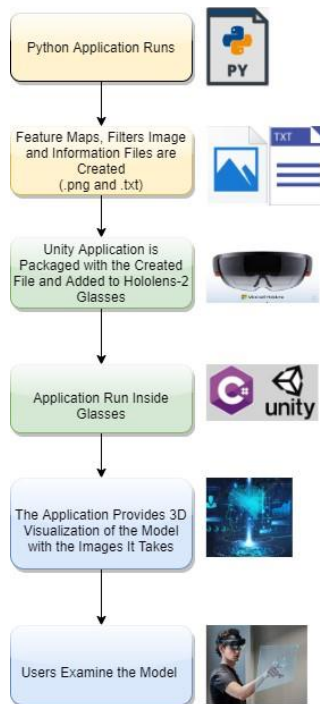
Figure 1 Stage of the Work

For visualization, mnist dataset was used on the lenet model like Figure 2.
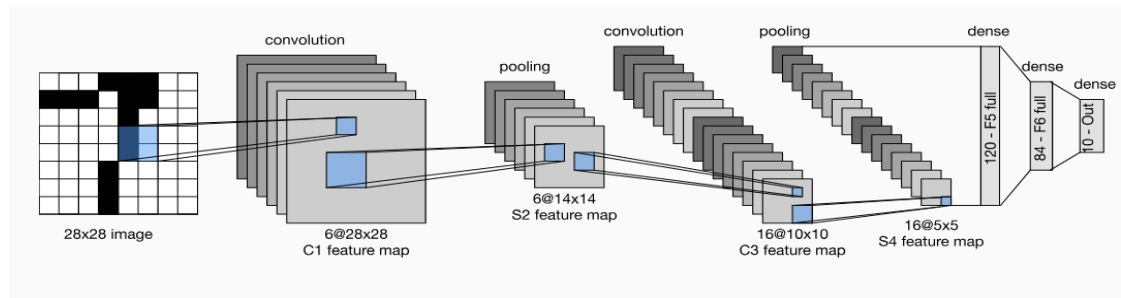
Figure 2 Lenet Model Architecture

4.2. Python Application

First of all, the curse model was created. It was trained with the Mnist dataset. It was then tested with sample data. The filters used at this stage were saved as png files (Figure 3). In addition, the weight values of these filters are stored in the txt file (Figure 4). During the testing phase with sample data, the feature maps in the layers were also recorded. Each numerical value of the Mnist data set was tested. The feature maps of all these values have been recorded .
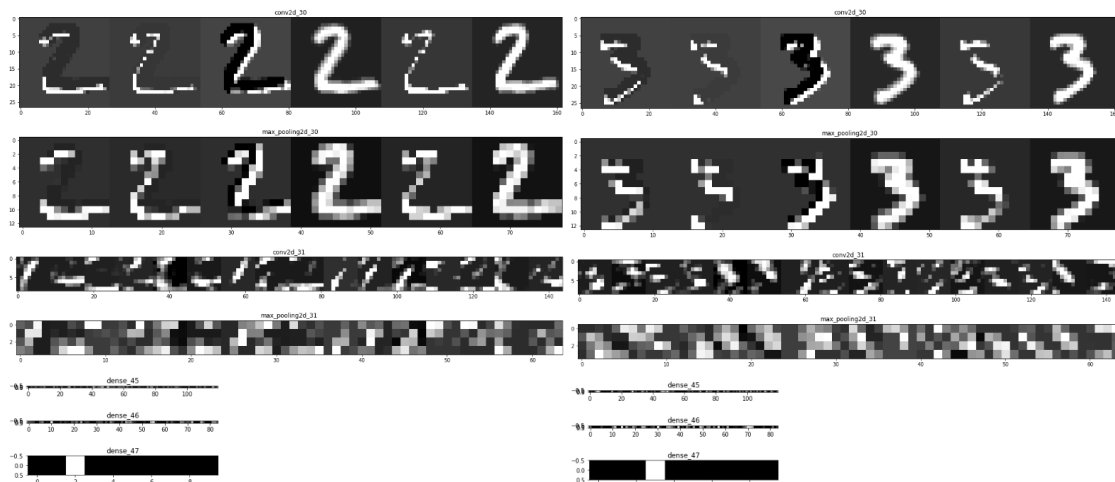
Figure 3 Saved Feature Maps In Each Layer

```
conv_1 [[[ 0.1436145   0.36392194 -0.35958698  0.2831421   0.42979705
   -0.17651269]]

 [[ 0.41274172  0.5671656   0.31445003  0.40183255  0.23169805
   -0.06156456]]]

[[[ 0.37006384  0.33062437  0.3566598  -0.17446826 -0.11316572
    0.24071108]]

 [[-0.3338682   0.2797875   0.4647417  -0.1130608   0.47212687
    0.58496   ]]]


conv_2 [[[-0.0035638   0.01857955  0.00345579 -0.03389946  0.08544827
   -0.02641048  0.04425801 -0.07087898 -0.13192365  0.09264576
   -0.02786475 -0.10374412  0.03902938 -0.08340353  0.03945175
   -0.05052324]
  [-0.11797303 -0.02329039  0.06379768 -0.05451531 -0.12430871
   -0.0365213   0.10436592 -0.05729429 -0.15864901  0.09168959
    0.07641833 -0.01234336 -0.10829927 -0.02704247 -0.03722082
    0.01436257]
  [-0.04601551  0.00257322 -0.04086462  0.08437762 -0.02252564
    0.04007699 -0.01719958  0.05571664 -0.00258061  0.09509603
   -0.02107869 -0.09936313 -0.05063814  0.11793681 -0.03177359
    0.01895607]
  [-0.10492108  0.04813968 -0.01049864 -0.10914589  0.04594256
   -0.09280792  0.01913452 -0.08232185 -0.18332808 -0.11007209
   -0.07392413 -0.06140407 -0.10403623 -0.01369665  0.01005093
   -0.02693376]
```

Figure 4 Weights Of Saved Filters

4.3. Unity Application

For Fully Connected Layers, the information received is given to the variables held by the PerceptronManager script created in Unity, as shown in Table 1. When the application is run, the perceptron prefab, which represents the layers, the number of neurons in the layers and their weights.

Table 1 Entering Parameters for Network Structure in Unity Editor

PerceptronManager	
Perceptron Prefab	GameObject
Layer Padding	Float
Perceptron Padding	Float
Input Layer Perceptron Count	Int
Output Layer Perceptron Count	Int
Hidden Layer Perceptron Count	Int
Hidden Layer Count	Int
Start Position	Vector3

• MRTK library was used to run on Microsoft Hololens-2.
• The user was offered a choice of test data. (In the next study, the user will be allowed to draw with his own hand.)
• Volume was given to visualize the size of each layer (Figure 5 – Figure 6).
• Layer information was written over the layers.
• Filters visualized(Figure 7).
• Weight information was written as each filter scanned.
• When each layer was clicked, the feature maps of the layer were visualized (Figure 8 – Figure 10).
• To make it more impressive, animations were used while filters scanned inputs and layers were clicked.
• When focusing on the fully connected layers, connections can be visualized (Figure 9).
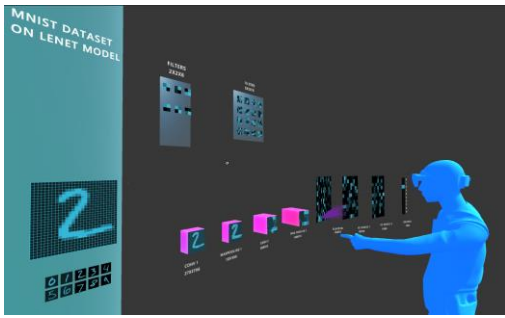
Figure 5 Visualization All Layers on LenetModel

Figure 6 Visualization All Layers on LenetModel
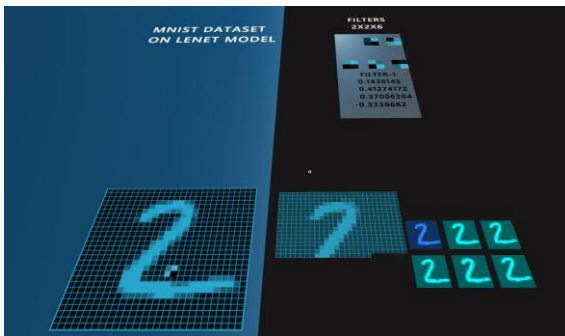
Figure 7 Filters and Opened Feature Maps After Click

Figure 8 Feature Maps
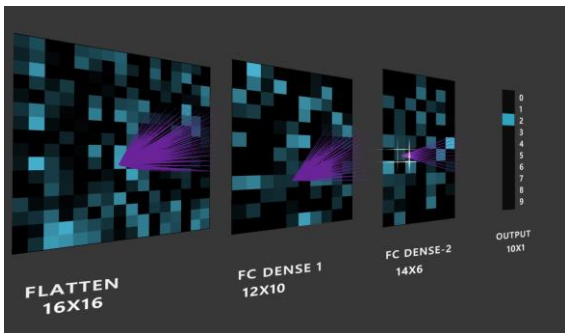
Figure 9 Fully Connected Layers and Output Layer Visualization
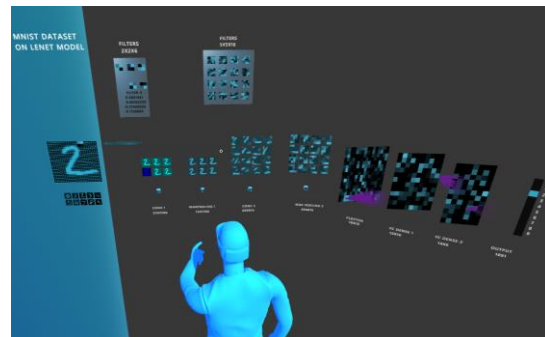
Figure 10 All Layers Opened

Figure 11 User Viewing the Network Structure on Hololens-2

4.4. User Tests

By including real user data in the design process and measuring the benefits or harms of each change, it is necessary to fully understand and explain what effects the changes have on users' behavior.

User research should identify the most important statistical information and tools needed to measure user experience, providing guidelines on the practical aspects of quantitative analysis. Statistical theory should be linked to practice and user research should be measured. It can be done by the following methods:

- summarize data and calculate margins of error,
- determine appropriate sample sizes,
- standardize usability surveys,
- resolve controversies in measurement and statistics [12].

In this study, the user group has been created that include 20 people working in artificial intelligence. The network structure was tested them on Hololens 2. Some questions are asked the users. The system was compared with a 2D version of this application running on a computer. Sum(The Single Usability Metric) was used for user testing. It is the representation of four basic parameters that facilitate the usability of a task or system with a single average statistic.
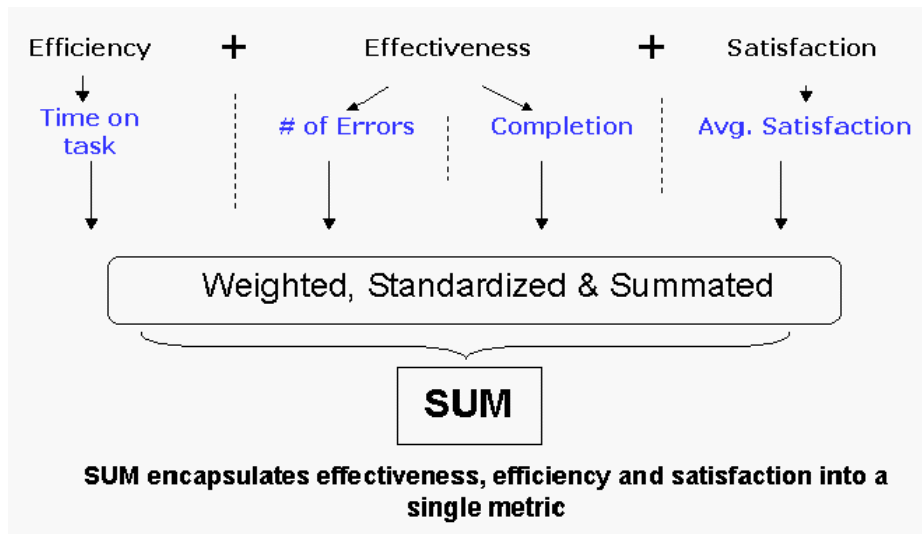
Figure 12 SUM Model

Table 2 Title Distribution of Employees

	Groups	Frequency	Percent (%)
Title	Software Engineer Interested In Data Science	10	50
	Software Engineer Interested In Augmented Reality	4	20
	Software Engineer Interested In Augmented Reality and Data Science	2	10
	Software Engineer not Interested In Augmented Reality and Data Science	4	20
	Total	20	100

Table 3 Professional Experience Distribution of Employees

	Groups	Frequency	Percent (%)
Professional Experience	1-5 years	10	50
	6-10 years	10	50
	Total	20	100

First of all, 2D application was tested by users and results were saved. There are 2 tasks that users do. After that 3D application was tested. SUM values were obtained.

Task 1: Open the application on the PC and select the test data. Which part of the test data is focused on in the 2nd convolution layer?
Task 2 : Which convolution filter detects certain features in the data more effectively on PC?
Task 3 : Open the application on the Hololens 2 and select the test data. Which part of the test data is focused on in the 2nd convolution layer?
Task 4: Which convolution filter detects certain features in the data more effectively on Hololens 2.

Every single user did this task. Completion, error size and times were saved. For Satisfaction ASQ (After-Scenario Questionnaire) model was applied as shown in the Table 4. An After-Scenario Questionnaire is a tool designed to gather feedback and insights from participants or observers after they have experienced a particular scenario, event, training session, or any other structured activity. The purpose of the questionnaire is to assess the effectiveness of the scenario, identify strengths, pinpoint areas for improvement, and collect subjective opinions from those involved. By collecting responses to these questions, organizers or facilitators can gain valuable insights into the strengths and weaknesses of the scenario. The feedback can be used to refine future scenarios, enhance facilitation techniques, and ensure that participants' needs and expectations are met. Overall, an After-Scenario Questionnaire is a valuable tool for continuous improvement and refining the design and delivery of scenarios or events [13].

Table 4 ASQ Questions

	For each of the questions below, circle the answer of your choice .
1.	Overall, I am satisfied with the ease of completing the tasks in this scenario.
	strongly disagree <--------------------------------------->strongly agree not applicable 1 2 3 4 5 6 7 NA
2.	Overall, I am satisfied with the amount of time it took to complete the tasks i n this scenario .
	strongly disagree <--------------------------------------->strongly agree not applicable 1 2 3 4 5 6 7 NA
3.	Overall, I am satisfied with the support information (on-line help, messages , documentation) when completing the tasks ?
	strongly disagree <--------------------------------------->strongly agree not applicable 1 2 3 4 5 6 7 NA

Table 5 ASQ Score for Task 1 and SUM Model Results

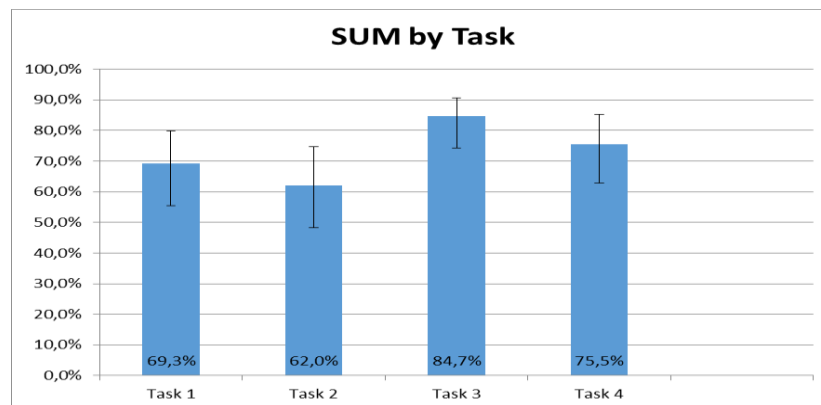| TASK -1	Open the application on the PC and select the test data. Which part of the test data is focused on in the 2nd convolution layer?

	ASQ QUESTIONS AFTER TASK(For Measuring User Satisfaction)
1	Overall, I am satisfied with the ease of completing the tasks in this scenario.
2	Overall, I am satisfied with the amount of time it took to complete the tasks i n this scenario .
3	Overall, I am satisfied with the support information (on-line help, messages , documentation) when completing the tasks.

USER	1	2	3	Satisfaction	Satisfaction		USER	Satisfaction	Completion	Errors	Times
1	5	5	5	15	5		1	5	1	1	70
2	5	5	5	15	5		2	5	1	0	75
3	6	5	3	14	4,66666667		3	4,66666667	1	0	74
4	4	5	5	14	4,66666667		4	4,66666667	1	3	80
5	4	6	5	15	5		5	5	1	0	73
6	5	4	3	12	4		6	4	1	0	62
7	5	4	4	13	4,33333333		7	4,33333333	1	0	65
8	1	4	5	10	3,33333333		8	3,33333333	0	3	105
9	6	6	5	17	5,66666667		9	5,66666667	1	0	58
10	6	5	3	14	4,66666667		10	4,66666667	1	0	63
11	4	1	4	9	3		11	3	1	3	110
12	1	1	5	7	2,33333333		12	2,33333333	0	1	121
13	5	2	4	11	3,66666667		13	3,66666667	1	2	105
14	5	4	4	13	4,33333333		14	4,33	1	1	89
15	1	4	3	8	2,66666667		15	2,67	0	2	78
16	6	3	5	14	4,66666667		16	4,66666667	1	1	92
17	6	5	5	16	5,33333333		17	5,33333333	1	0	58
18	6	2	6	14	4,66666667		18	4,66666667	1	4	132
19	6	6	4	16	5,33333333		19	5,33333333	1	0	70
20	5	5	4	14	4,66666667		20	4,66666667	1	2	88

SUM MODEL (Single Usability Metric)

Table 6 Result of User Tasks

Task	Low		High	Completion	Satisfaction	Time	Errors	Graph Low	Graph High
Task 1	55,4%	69,3%	80,0%	80,8%	63,9%	82,9%	43,0%	13,9%	10,7%
Task 2	48,2%	62,0%	74,6%	58,8%	44,7%	61,0%	81,1%	13,9%	12,6%
Task 3	74,3%	84,7%	90,7%	89,6%	93,0%	90,3%	57,0%	10,4%	6,0%
Task 4	62,7%	75,5%	85,2%	72,0%	58,2%	87,9%	77,7%	12,8%	9,6%

Table 7 Result of Tasks

As a result of the answers received, it was determined that users generally had difficulty in using Hololens in the beginning. However, it was seen that everyone was eager to use the new system. Looking at the answers received from the questions, it was seen that the users gave answers that were open to improvement in 3D interfaces.

They commented that being 3D and interactive provides ease of understanding for more complex networks. In this sense, they stated that they wanted to use 3D.
In the continuation of the study, it is aimed to develop the system to visualize the model structure based on this foundation. At this stage, a structure has been presented to users to form ideas. UX studies will continue.

5. CONCLUSIONS

As with every information system, deep learning systems require interaction with the user. This interaction can occur at any stage of an artificial intelligence system. For example, there is a close relationship with the expert during data collection for the development of supervised learning systems. While some systems use classical 2D (two-dimensional) interfaces in this regard [14, 15, 16], augmented reality can play an important role, especially in spatial data collection applications [17, 18]. Virtual and augmented reality methods can also provide useful interaction in cases where the data is partially created by artificial methods.

There is also machine-human interaction during model training. Manual adjustment of training parameters by the expert requires effective presentation of the training result to the user [19, 20]. Visual interaction is frequently used in this field [21] and it is thought that the use of augmented reality will be especially useful in evaluating the performance of models that produce spatial data [23].

On the other hand, augmented reality interfaces can also be used during the application of deep learning algorithms. While the outputs of deep learning-based systems cannot often be used directly in automatic decision-making (in case of errors), user interfaces have the potential to increase the usability of such systems. These systems [22, 23], which use artificial intelligence systems as a feature that enhances human capabilities, emerge as an area with high potential for augmented reality, especially in cases where spatial data is processed.

As a result of the research, 2-dimensional interfaces were examined, focusing on their intended use and what could be done in 3 dimensions. In this sense, considering the graphical and network structure visualization, it was decided that visualizing the network structure would be more useful

for users. By visualizing the layers, weights and hyperparameters of the model with Hololens, it draws the user into the event, increasing his awareness and making it easier to make decisions.

Additionally, users will not only be able to visualize the network in this system's limitless virtual space but also find its graphical representation in the same environment afterward.

For these purposes, an example network structure was created with the application made on Unity. For this purpose, firstly, the Lenet model was created with Python code, trained with the mnist data set, and tested with sample data. The feature maps that emerged during this testing phase were recorded. In addition, the filters used in the layers, weights in the Full connected layers, and hyperparameters were also recorded. Visualization was made on Unity with all these saved files. The application was first run as a desktop application and then on Hololens-2, a mixed reality headset. Applications were tested separately with 20 people. The usability of the application was measured using the SUM model. The conclusion reached through the answers was that users were willing to use this system and their awareness of 3 dimensions was undeniable. As a result, these systems can be used as artificial intelligence systems that increase human capabilities.

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